# RATIONAL DECISION MAKING IN EARLY URBAN DESIGN BASED ON UNCERTAIN PERFORMANCE PREDICTIONS

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# RATIONAL DECISION MAKING IN EARLY URBAN DESIGN BASED ON UNCERTAIN PERFORMANCE PREDICTIONS

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In loving memory of my sister, Rania Al-Hashim (1997-2018).

Dedicated to my *Amma* (Amina Yusuf) and *Mummy* (Bilquees Ismail)

You always believed in me.

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# LIST OF SYMBOLS AND ABBREVIATIONS

| | |
|---|---|
| $A_D$ | DuBois surface area of the assumed person ($m^2$) |
| AEC | Architecture, Engineering Construction |
| $A_f$ | floor area ($m^2$) |
| $A_g$ | total area of glazing ($m^2$) |
| AHP | Analytical Hierarchical Process |
| $A_p$ | projected area of a person exposed to direct sunlight ($m^2$) |
| ASHRAE | American Society of Heating, Refrigerating, and Air-Conditioning Engineers |
| $A_{sol,k}$ | effective solar collecting area of surface k ($m^2$) |
| DOE | Department of Energy |
| $E_d$ | horizontal diffuse illuminance (lux) |
| $E_{del}$ | Delivered energy ($kWh/m^2$) |
| $E_{diff}$ | diffuse solar energy from sky vault |
| $E_{dir}$ | direct beam solar energy coming directly from sun |
| $E_g$ | horizontal global illuminance (lux) |
| $E_i$ | illuminance level inside the space on horizontal working surface (lux) |
| $E_o$ | extraterrestrial normal illuminance (lux) |
| $E_p$ | Primary energy ($kWh/m^2$) |
| EPC | Energy Performance Calculator |
| $E_{ref}$ | solar energy reflected upward from the floor |
| ERF | Effective radiant field ($W/m^2$) |
| $E_{solar}$ | Shortwave solar radiant flux on the body surface |

| | |
|---|---|
| EUI | Energy Use Intensity |
| $\varepsilon$ | classification of sky clearness |
| F | clearness function sensitive to seasonal changes |
| $\boldsymbol{f}_{bes}$ | fraction of body exposed to sunlight |
| $\boldsymbol{f}_{eff}$ | Fraction of body surface exposed to radiation |
| $F_{sh,ob,k}$ | shading reduction factor for external obstacles |
| GA | Genetic Algorithm |
| GVF | ground view factor |
| $h_r$ | Radiation heat transfer coefficient (W/m$^2$ K) |
| $H_{tr}$ | Heat transfer coefficient of the building by transmission (W/K) |
| HVAC | Heating, Ventilation and Air Conditioning |
| $H_{ve}$ | Heat transfer coefficient of the building by ventilation (W/K) |
| $i$ | incident angle on the façade |
| $I_d$ | diffuse irradiance (W/m$^2$) |
| $I_{diff}$ | diffuse sky irradiance on horizontal surface |
| IES | Illuminating Engineering Society |
| $I_n$ | normal irradiance (W/m$^2$) |
| $I_{on}$ | extraterrestrial normal incidence irradiance (W/m$^2$) |
| $I_{TH}$ | outdoor total horizontal direct and diffuse irradiance (W/m$^2$) |
| $K_d$ | Diffuse efficacy (lm/W) |
| $K_g$ | Global efficacy (lm/W) |
| LHS | Latin Hypercube Sampling |
| $m$ | optical air mass |

| | |
|---|---|
| MC | Monte Carlo |
| MRT | Mean radiant temperature ($^oC$) |
| $\eta_{C,ls}$ | dimensionless loss utilization factor for heating |
| $\eta_{H,gn}$ | dimensionless gain utilization factor for cooling |
| PDF | Probability Density Function |
| PDF | Probability Density Function |
| PRD | Probability of relative difference |
| PRD | Probability of relative difference |
| PRD | Probability |
| $Q_C$ | Total cooling need (MJ) |
| $Q_{gn}$ | Total heat gain (MJ) |
| $Q_H$ | Total heating need (MJ) |
| $Q_{ht}$ | Total heat transfer energy (MJ) |
| $Q_{int}$ | internal heat gains of the whole building (MJ) |
| $Q_{nd}$ | Thermal energy needs ($kWh/m^2$) |
| $Q_{sol}$ | sum of the heat sources from solar sources (MJ) |
| $R_{floor}$ | floor reflectance |
| RH | Relative Humidity (%) |
| SRF | Shading Reduction Factor |
| SVF | Sky view factor |
| $t$ | Assessment time period (Ms) |
| $T_{db}$ | Dry bulb temperature ($^oC$) |
| *TF* | tilt factor |
| $T_{sol}$ | is total solar transmission |

| | |
|---|---|
| UTCI | Universal Thermal Climate Index |
| $w$ | atmospheric perceptible water content |
| WWR | Window-Wall Ratio |
| $z$ | solar zenith angle |
| $\alpha$ | azimuth angle |
| $\alpha_{LW}$ | Longwave emissivity/absorptivity |
| $\alpha_{SW}$ | Shortwave absorptivity |
| $\beta$ | solar altitude |
| $\Delta$ | sky brightness |
| $\Theta_e$ | mean external temperature (°C) |
| $\Theta_{int,set,C}$ | internal set point temperature for cooling (°C) |
| $\Theta_{Int,set,H}$ | internal set point temperature for heating (°C) |
| $\nu$ | Air speed (m/s) |
| $\rho$ | average reflectance of all room surfaces |
| $\tau$ | transmittance of glazing |
| $\psi$ | Confidence level |
| $\psi$ | Confidence level |
| $\phi$ | Decision maker's preference |
| $\phi$ | Decision maker's preference |

# SUMMARY

The world is currently undergoing the largest wave of urban growth in human history. More than half of the global population is now concentrated in urban areas, and by 2060 `two third of the expected population of 10 billion will live in cities. While accommodate this tremendous growth, reducing urban energy consumption of resilient and livable cities should be seen as associated priorities. Meeting these priorities head on requires complex decision-making at the early phase of urban design, when a large number of parameters are still undecided, and their level of uncertainty is high. The thesis proposes a rational decision framework that responds to these challenges for a specific set of measures within the following limited scope: energy efficiency in urban layout, indoor daylight level, network connectivity, outdoor public space visibility and thermal comfort.

The early stage of urban design is characterized by its iterative nature of repeated alternative generation (divergent phase), and alternative assessment and selection (convergent phase). Decision making occurs during or at the end of these phases with considerable uncertainty in the many as yet unresolved design parameters. Therefore, methods and tools applied during these phases should account for the iterative and unpredictable nature of later design evolution.

Currently there is no consistent support for rational decision making at the early stage of urban design. Typically, single deterministic predictions are generated based on assumed parameter values when in fact many of those parameters have not been decided yet.

This dissertation starts from a hierarchical structure that outlines consecutive steps in the design process by geometric output type. This is not the main focus of the thesis but merely a structuring principle that is employed by the rational decision framework. This framework supports the comparative assessment of competing design alternatives under uncertainty. This is the main focus of the research. It introduces explicit information about uncertainty in undecided design parameters and analyzes their effects on the confidence with which one design variant can be prioritized over another.

The approach is implemented in a Rhino-Grasshopper platform for five concrete performance measures: network connectivity, visibility in open space, outdoor thermal comfort, building energy consumption and daylight utilization. Low-resolution simulation models are developed for each of these measures to service the iterative nature of design with fast computation of results. The resulting models serve as normative substitutes for more accurate physics-based prediction models. The research has developed a systematic verification approach showing when these reduced order models are indeed as adequate for the targeted comparative analysis in early design as their high-fidelity counterparts.

In the comparative analyses of design variants, point values of inputs are replaced with probability distributions that quantify the expected variability (treated as design uncertainty) in later decided design variables using a Monte Carlo technique. Hence each generated outcome is a probability distribution that represents the uncertainty in the performance prediction of a design alternative under study. The performance predictions are the inputs into the decision making allowing the designer to make a rational choice of

one design alternative over a competing one. In the developed framework such decisions are driven by minimum required confidence levels that a decision maker is comfortable with when prioritizing a variant. As an associated issue the research tested the effectiveness of current rules of thumb and found that design choices that they suggest typically fall short of the confidence level required by the decision maker.

This dissertation introduces the methodology, the development of a framework for comparative analysis with embedded normative models (implemented as grasshopper components) and their execution in the current prototype.

# CHAPTER 1. INTRODUCTION

## 1.1 Background

Cities are both most vibrant productive human creations and one of the main sources of global environmental impacts, a reality that is proving to be more acute with time. As per UN's estimate, the number of city dwellers will grow until 2050 at a rate of five million per month, mostly by informal settlements and haphazard densification (Affairs, 2015), leading to urban-related greenhouse gas (GHG) emissions to be at an all-time high, with building energy consumption being the key contributor.

The world is currently undergoing the largest wave of urban growth in human history. More than half of the global population is now concentrated in urban areas (Figure 1.1-a), and by 2060 two third of the expected population of 10 billion will live in cities. To accommodate this tremendous growth, we expect to add 2.48 trillion square feet (230 billion m2) of new floor area to the global building stock, doubling it by 2060. This is the equivalent of adding an entire New York City every month for the next 40 years (2030, 2019).

Most of the world is projected to be built and rebuilt over the next two decades (Figure 1.1-b) with the energy and emissions patterns of this construction locked-in for many years (average building and infrastructure life span are 80 and 120, respectively). Today we have a once-in-a lifetime opportunity to address climate change by creating low-carbon and zero-carbon cities, districts and buildings.

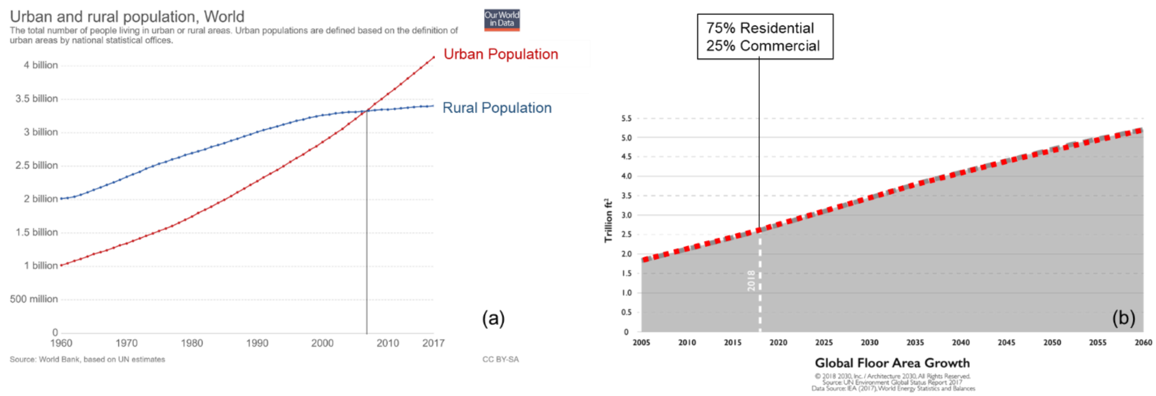



**Figure 1.1: (a) Urban and rural population of the world (1960-2017), (b) Global floor area growth (2005-2060).**

As per 2016 UN Habitat report, urbanization requires a coherent approach as challenges posed by urbanization have global ramifications, that if not addressed adequately, could jeopardize chances of achieving sustainable development. It is therefore necessary to shift cities and towns onto a sustainable development path as continuing along the current model of urbanization is no longer an option (Programme, 2016). Cities and towns can play a greater role in the sustainable development agenda, and for that they need to be better understood.

Timely updating urban planning and design regulations is a recurrent challenge for municipal governments, more so in recent years as the authorities are trying to aim for sustainable growth and ensure urban experience. We can no longer rely on traditional standards and practice that are based on historical patterns and outdated workflows, as they are not adequate for new sustainable development agenda. New approaches in urban development should move away from traditional, prescriptive methodologies. One alternative is a performance-based approach to design, establishing specific performance measures directly related to desired outcomes (Wilson, et al., 2018).

Performance-based approaches are composed of two components: first, criteria that describe the desired end result (goal), and second, methods to define standards used to state the acceptable limits of impact to ensure the desired end result. It is important to note that performance-based planning is not a new concept, it has been adopted by many local governments in the Unites States in 1970, Australia in 1997 and New Zealand in 1991 aiming to integrate planning processes with effects of development on environment (IPA section 1.2.1). However, this approach was subsequently either abandoned because of inadequate technology to follow-up and heavy administrative required burden or was hybridized with traditional planning methods (Baker, et al., 2006). One of the main reasons that also lead to the failure of application of this approach was absence of proper management, it is important to note that in a performance-based approach, proper design process workflows should be taken into consideration along with properly defined performance requirements. Designers often seek to fulfill performance requirements but tend to forget about a proper framework for design exploration and assessment, without which this approach cannot be applied (Augenbroe, 2019).

Urban design is a complex decision-making task that involves interdependencies among variables and among multiple performance measures, making it difficult to come up with a ‘general guidance’. There still is a need for appropriate urban design decision support, especially methods and tools for the early stages of design when many design parameters have not yet been decided upon. A framework is needed that would not only allow decision makers to integrate aspects of performance into their design process, but also lead them towards desired performance levels and give them enough confidence in their decisions.

In order to evaluate the current performance-based approach and design frameworks at the early stage of urban design, we first need to investigate the nature of the design ‘process’ independently from the nature of design ‘output’. This will be done by reviewing and defining the early stage of urban design, also known as conceptual design, along with its components, followed by an overview of the current performance-based methods and frameworks applied to this phase.

## 1.2 Review of Early Stage in Urban Design

Conceptual design is an early stage in the design process that involves the generation of solution concepts to satisfy the functional requirements of a design problem. Conceptual design, being one of the early stages of design is characterized by information that is often imprecise, inadequate, and unreliable. Apart from the observation that the recognition and generation of functional requirements and the generation of solutions are highly coupled in this stage, there is little understanding as to how this is done, and consequently little support is available (Chakrabarti & Bligh, 1996).

Early design stage or Conceptual design is one of the most important and influential stages of a product development process (Figure 1.2), it is the phase where engineering science, practical knowledge, production methods and the commercial topics need to join and where the most important decisions are taken (French, 1985). Because of its importance, it is evident that the early stage of design must use all available means and resources to help developing better and more innovative concept design solutions (Horvath, 2005).

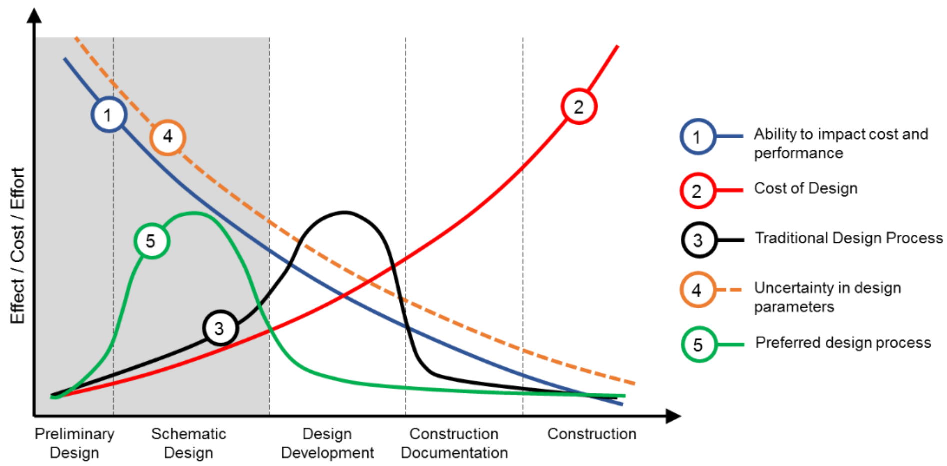



**Figure 1.2: Design stages, based on MacLeamy curve (2004)**

Urban design is fundamentally creative and therefore distinctive to each specific context in which it is implemented. It may be understood as a 'process', which refers to a method, procedure or series of actions or events that lead to the accomplishment of some result (Atkin, et al., 2003). At the early stages of design, conceptual alternatives are proposed, assessed based on given requirements, the main aim of this stage is the generation of promising concepts that can later on be developed into promising solutions that can be further refined in the detailed design phase.

The urban design process is delineated by a complex set of decisions involving various stakeholders, tasks, issues and feedback loops that form and influence urban design projects over time (Boyko, et al., 2006). Urban design is also an iterative process of urban development and change that is shaped, controlled and contested by visual, functional and experiential qualities of places and spaces (Rowley, 1994).

Since urban design as any design process is an incremental practicing and learning process, it becomes an impossible task to come up with a 'proper' solution in one shot, instead a series of divergent and convergent steps has been proposed by Liu (Lui, et al., 2003) to increase the possibility of creating better end products:

- During a Divergent step, a range of concepts is generated.
- During a Convergent step, generated concepts are evaluated and selected.

In case of divergent step, the aim is to develop promising concepts, which requires generating a wide range of concepts and ensuring that valuable ones do not get left out. A design problem usually has many solutions; therefore, if one could explore a solution space larger than is presently possible, there becomes a scope for producing improved designs (Chakrabarti & Bligh, 1996). In current practice, a divergent step mostly relies on a designers' experience, who often disregard promising options based on their personal experience which is sometimes biased towards using certain kinds of solutions perhaps because they have used them before. The convergent process consists of concept evaluation and selection, in which alternatives are identified that best fulfill the requirements. Currently the assessment methods vary from 'none' to 'advanced'. Either the designers fully rely on their experience to evaluate alternatives, or use more or less advanced simulation tools for it, which also vary from simple simulation models that require few inputs, to high-order models requiring extensive number of inputs many of which are typically not available at the early design stage, which is most cases is acquiesced through commonly accepted default values. In either case, single deterministic values are assumed for design parameters at a stage when many parameters have not been decided yet and could in fact take a range of values as yet unknown.

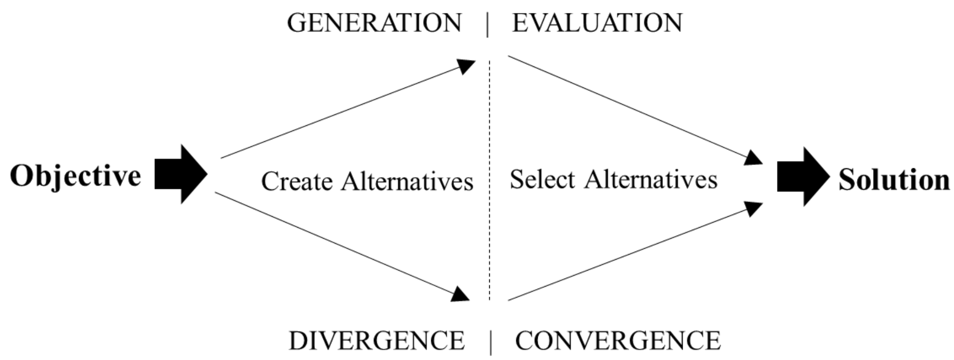



**Figure 1.3: Divergent and Convergent phases of Conceptual Design Process**

At the early design stage, there is high level of unknowns or uncertainties from different sources, most of which is from lack of information about how the design will evolve. Taking these uncertainties into consideration at early design stage inserts a more conscious view to early stage design that is lacking in current approaches. It should be recognized that many designers have a level of experience that enables them to anticipate the effect of the variability of as yet undecided parameters in their decision making. But in those cases, a high dose of subjectivity can creep in. It is the purpose of this thesis to add rigor and quantification, thus removing some level of subjectivity, and avoid the application of rules of thumb where in fact none have been verified.

## 1.3 Summary of Problem & Motivation

Complex urban design problems need to deal with many variables which are uncertain in the early design phase. Urban design is a compound problem, in which information, problem constrains, and criteria change during the process. A situation in which generating one solution is a challenge, let alone exploring multiple options. The biggest challenge to overcome in urban design is assessing future performance of a new design alternative and exploring simultaneously sufficient number of alternatives to be able to select amongst them based on a chosen set of performance requirements or targets.

Our inability to cope with the complex problems and to develop adequate alternatives, in part, is rooted in the design situation. The urban designer does not deal with a problem, but rather with a problem situation, in which he needs to identify the criteria which will prove relevant. Along with developing alternatives, designers also need to test their performances, and predict how a proposed alternative will influence and be influenced by the original design situation which one is attempting to modify.

Beyond the complex task of design, there are other limitations, such as: time restriction, difficulty in identifying errors before design is well advanced, high cost associated with altering or abandoning designs on which much time has been spent.

This situation drives us to repeatedly attempt to develop models of the design process in hope of increasing our understanding by precisely describing the generic logic that governs this process. However, this alone is not enough, we must strive to reduce the increasingly complex task to somewhat more manageable proportions.

Design decisions are frequently made based on inadequate data, and these decisions commit us to future actions. They need to be reconsidered in light of new knowledge, and many times require that the designer return to an earlier stage of the process. This iterative and dynamic nature of design requires the process to be simultaneously active along several fronts; sequence of change may appear random, or jumping back and forth, or may progress from the general to the specific, or run the other way around (Borrego, 1968).

Urban design in the early design stage -as any other design- is iterative, complex and uncertain, however there are methods applied both for the divergence and convergence phases that don't fully consider these characteristics of the design process. The following are noted shortcomings of traditional urban design approach in three major aspects:

**A. Concept Generation Phase:**

The current approach of urban design is a more or less systematic method of alternative generation, solely dependent upon the designer's experience, biases and preferences, leading to narrowing of the design space, hence a range of possibilities are left unexplored.

a) *The number of generated alternatives is limited:* Due to limitations in time, budget and technology, only a narrow range of alternatives are fully explored. Furthermore, humans have specific and limited cognitive structures that constrain their behavior as searchers and conceptualizers of the problem space (Woodbury & Burrow, 2006).

b) *Designers tend to choose a path that is most familiar to them.* An experience-based approach –an approach currently most used in urban design- highly depends on the ability to "know how to design", which involves high subjectivity and can threaten selection of good solutions, as designers end up choosing alternatives they are most familiar with or a direction that they identify with the most.

**B. Concept Assessment Phase:**

Traditional design approaches incorporate measurable criteria in advanced phases of design and not in the early phase. Convergence currently is used as a validation phase for specific design option, rather than means of exploring the potential of multiple options. Alternatives are not assessed in the early design phase for the following reasons:

a) *Urban design is a complex design problem with multiple performance objectives:* In urban design, several disciplines are involved with different performance objectives, some quantifiable and some only qualitatively specified. An effective method would be one that considers complexity of urban design problem and provides a systematic way for exploring the design space.

b) *Multi-objective nature of urban design:* Urban design as mentioned earlier is multi-discipline problem and is about fulfilling many requirements at the same time (Augenbroe, 2019), making analysis of design alternatives a complicated task, as it involves many participants with varying preferences.

**C. Design Uncertainties:**

Current performance evaluation methods and tools are used with deterministic inputs and generate deterministic outcomes for design alternatives with decided parameters and hence don't take into account the uncertainty associated with a lack of information in the early design phase.

a) *Uncertainty in performance prediction:* Due to multiple uncertainties in design parameters during the early design stage, outcomes are also uncertain, making a deterministic analysis of performances questionable. The complex and ill-defined nature of urban design, particularly in the early design phase makes it difficult to predict the value of performance measure as a deterministic outcome, as this will most probably not remain valid after design proceeds in unpredictable directions.

b) *Large number of undecided parameters:* In early design there are multiple undecided parameters, hence the information to assess and predict multiple performance measures (such as energy performance and outdoor thermal comfort) is insufficient. The lack of information is mainly associated with not knowing how design will evolve after the early design phase.

This research does not intend to find the most optimal urban design solution by minimizing or maximizing a certain objective function. While optimization techniques can find the best solution for some parameters, its application in the early design stage is arguably misleading for the following reasons:

a) In process of urban design our objective is not to identify the most "optimal solution, instead the aim is to support more broadly feasible solutions that fulfill performance requirements, without inhibiting designer's freedom and creativity to move towards in alternative directions.

b) A design approach is not assessed by the end product, but rather by the enabling design progress. A good design approach is the one that helps designers in the process of design through understanding the problem itself, relations between the parameters, effects of one decision over decisions that have not yet been made. Optimization techniques are typically product-centric and do not help designers in understanding and breaking down a complex design problem.

c) Urban design, especially in the early stages is an iterative process in which many changes might occur in the design parameters. Conducting a full design exploration and analysis at each stage would incur high cost and abundant time, making it an impractical approach.

## 1.4 Urban Application Scope

This thesis mainly focuses on the area of urban fabric, which is similar to the scale and definitions used for plan unit, as used by Caniggia (Moudon, 1994). The urban fabric consists of a collection of islands, as well as the network that surrounds these islands and is required as access to the islands (access streets). The area of an island, also referred to in the traditional city as an urban block, is comprised of lots and non-built space designated for building (Figure 1.4). The boundaries of the fabric are drawn in the middle of the access streets. In circumstances where there is no street, the boundaries of the fabric are set by the lot boundaries. The size of the fabric is determined by the level of homogeneity (spread) of different islands within the fabric (Berghauser Pont & Haupt, 2009).

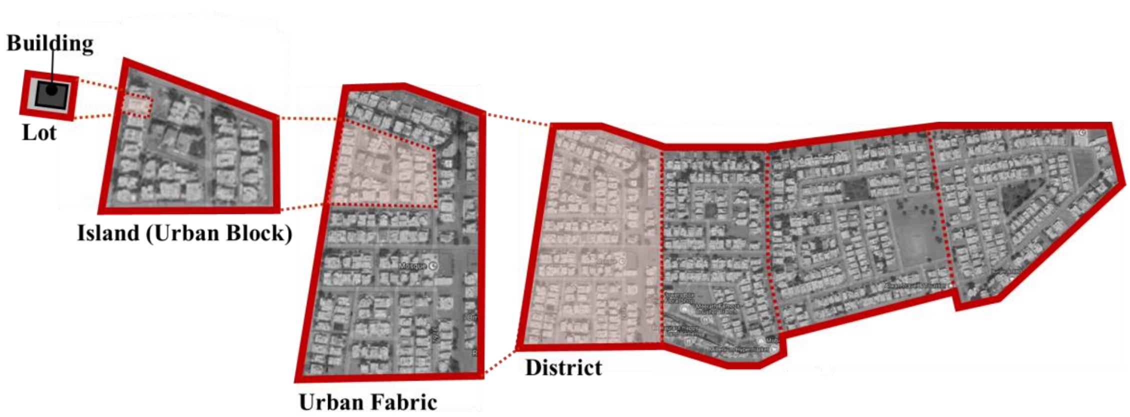



**Figure 1.4: Urban aggregation levels: District, Fabric, Island, Lot.**

## 1.5 Research Hypothesis & Methodology

A guiding framework is needed for early stage urban design decision making, which will help the designers find and choose the values of design parameters that would lead them to a targeted performance with greater likelihood. A framework should support design exploration, in which a designer is capable of intervening in the search process, extract knowledge from generated solutions to make better-informed decisions and allow designers to make iterative design decisions by accounting for unknowns at different decision points, hence showing how certain decision and their involved parameters can impact other interrelated parameters.

The research intends to address the need of this guiding framework by responding to the following overarching question:

> **Research Question:** In the early phase of urban design, what framework can assist in performance prediction under uncertainty and can hence support rational design decision making? The purpose is to inject rationality where designers make tradeoffs between competing alternatives, allowing them specifically to make judgments about the likelihood that a proposed alternative meets specified performance target and/or has sufficient probability to outperform competitors.
>
> This question can be subdivided into four sub-sections:
>
> **Question (1)**: How to account for design parameter uncertainty in the creation of the option space and ensuing performance predictions and evaluations at different decision points in early design?

**Question (2)**: What methods and tools can be used for performance prediction at the early urban design stages for comparative analysis and decision making?

**Question (3):** How can designers make informed decisions with confidence?

The main goal of this research is to support proper evaluation of design alternatives in early design and assist the designers in their selection and decision-making, thereby improving the design process as a whole. It is anticipated that the large body of existing work in generative methods (dealing with design option generation in research question 1) will eventually be married with the research presented in this thesis. As alternative generation itself is not within the scope of this thesis, a temporary substitute is used in that this thesis starts from the assumption that designers have generated competing design variants without specifying how this generation process is conducted or supported. The proposed approach considers the iterative nature of early stage urban design and proposes a step-by-step approach in making decisions and updating information as new decisions are made. In this thesis the scope of the study is the urban fabric scale, defined by the major street network and consisting of multiple urban blocks.

This work is driven by two major hypotheses:

**Hypothesis (1)**: In comparison to current traditional urban design methods, the proposed performance-based framework helps the designers in the design process by providing them with more guidance, in particular by adding rationality in the selection among competing alternatives. Early design will thereby become more effective.

**Hypothesis (2)**: Application of the proposed approach can lead to higher probability of achieving energy efficient urban layouts with comfortable and livable outdoor public spaces, which is the central urban performance scope of this thesis.

Both hypotheses cannot realistically be proven or refuted in general without large scale study of real design processes. As a prelude to this it will be "validated" under in-vitro conditions in several case studies (Chapters 4 and 5).

## 1.6 Intellectual Contribution of this Dissertation

The performance scope of this work is limited to: energy efficiency in urban layout, indoor daylight level, network connectivity, outdoor public space visibility and thermal comfort. The proposed framework will have the following contributions to early stage urban design processes:

1. It accounts for the complexity of urban design by proposing a step-by-step process in which decision are made and subsequent influence of decisions is revealed.
2. It is computationally efficient by embedding reduced order models that allow for making rapid changes and informative exploration of the design option space.
3. It considers design uncertainty of parameters in the early design stage though presenting the outcomes as probability distributions as opposed to deterministic outputs, hence increasing the chance of getting to the preferred target.
4. It computes the confidence level associated with different design options in achieving set performance targets, so the decision maker can make risk conscious decisions related to adopting or rejecting design alternatives.

## 1.7 Thesis Structure

Following this chapter, the study first introduces a view on the urban design process that directs future work, its decision-making aspects, specifically in the early design phase, highlights performance-based design methods and explores role of uncertainties in the urban design process. Chapter 3 overviews current workflows in alternative generation and assessment, existing performance analysis tools used in urban design and emphasizes the necessity of accounting for design uncertainty in design exploration and analysis. In chapter 4, the thesis methodology is explained, along with performance indicators used for assessing the urban fabric with an illustrative case study for each indicator. Then in chapter 5, the study demonstrates the feasibility of proposed approach by applying it on real-life case studies. Chapter 6 compares the proposed method with a currently used rule of thumb along with an implementation of the proposed methodology in chapter 7. The thesis ends with concluding remarks and future work in chapter 8.

# CHAPTER 2. LITERATURE REVIEW

## 2.1 Design Decision Making

Design is the process by which a designer develops and/or selects the means to achieve a set of objectives, subject to a set of constraints; and a design object is a satisfactory solution to this problem (Tate & Nordlund, 1996). Therefore, design can be looked at as a process of decision-making. Based on decision-making theory, a decision can be defined as a choice taken by individual. Unlike problem solving, in which we get an answer, that can either be wrong or right, decision-making does not have a specific answer, rather an outcome, that can be evaluated and the ‘goodness’ of this decision depends on its consistency with the available choices, and the decision maker’s beliefs on the possible outcomes of those choices, and his preference over his beliefs (Hazelrigg, 2012). Decision theory in realm of design is a framework for thinking logically about choices in the presence of uncertainty in outcomes of choices (Rezaee, et al., 2014).

As mentioned in the earlier section, the early stage of design is considered an important phase in the design development process, as it influences all subsequent phases leading to the end-product (Chong, et al., 2008). Making a poor selection in early design stage can rarely be compensated at later design stages, hence having a performance assessment method based on forward projection in early design is crucial.

## 2.2 Performance-based Design Process

Performance-based design is a process in which a design team develops performance goals and generates and analyzes options in order to seek high performing solutions (Deru & Torcellini, 2004). In performance-based design, design guidance is defined as the measurable and replicable impact of a design process in the determination (generation and selection) of design solutions.

Clevenger and Haymaker (Clevenger & Haymaker, 2009) defined design components and their relationships as shown in Figure 2.1. Terms '*Objective Space*' '*Design Space*', '*Impact Space*' and '*Solution Space*' are introduced to describe performance-based design spaces. Objective space consists of stakeholders, goals, preferences and constrains for a project. Stakeholder is the party with an interest in the selection of alternatives. Goals are declaration of intended properties of alternatives. Preferences is the weight assigned to a goal by stakeholder. Constraint is the limit placed on variable. Design space consists of set of possible design options that meet design constrains. Design option is defined by the unique combination of design variables, which represent individual decisions made by a designer. Impact space consists of impact calculation for design options, impact is an alternative's estimated performance according to a specified goal and it can either be easy or difficult to quantify. In this space alternatives are compared, so it is necessary to have universal performance units. Solution space consists of set of design values generated. Design value is a function of an option's impact and stakeholder preference relative to the goals.

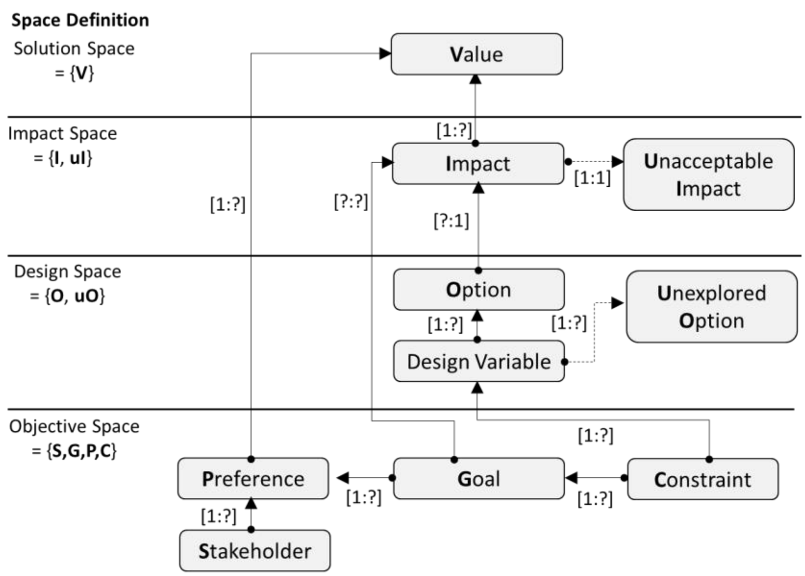



**Figure 2.1: Process Map for Performance-based Design, based on (Clevenger & Haymaker, 2009)**

In Figure 2.2, components of performance-based design as defined by (Clevenger & Haymaker, 2009) are represented. Design variables along with their constrains lead to option creation, also known as '*Design Space*'. Based on the assessment of this '*Design Space*', an '*Impact Space*' is created, which is the probability distribution of the output, representing all possible performances. Based on decision maker's preference, an '*Objective Space*' is defined, from which '*Solution Space*' can be extracted.

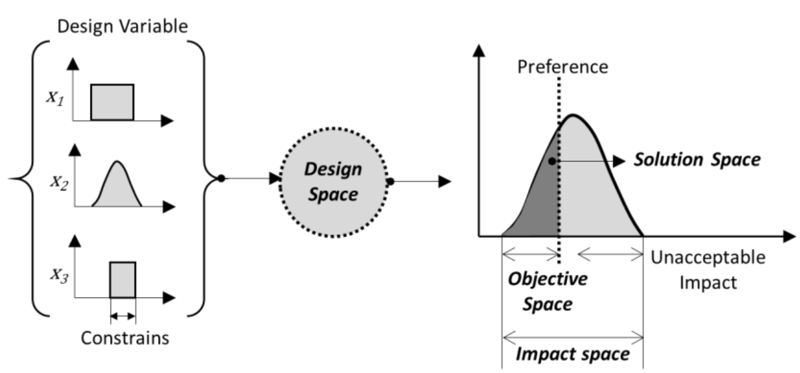



**Figure 2.2: Representation of Performance-based Design components**

## 2.3 Conceptual Design Phase

Urban design problems deal with multiple variables and data which are uncertain, abstract and heavily dependent on long range predictions. Further compounding the problem, information, problem constrains, and criteria will change or be altered during the design process. Making it difficult to generate even one solution for the problem, let alone coming up multiple possible alternative solutions (Borrego, 1968). One of the reasons for our inability to cope with complex problems is because of the design situation, as the urban designer is not presented with a problem rather a problem situation. Within this complex situation, the designer must identify relevant problems, develop designs and test their performance.

Urban design is a complex design situation, which always confronts resource limit. There is never enough time to perform more than an oversimplified analysis, there is also the difficulty of spotting faults before the design is well advanced and as design proceeds. Altering or abandoning designs on which time has been spent can be costly. It is this situation that drives us to repeatedly attempt to develop models that can assist us in the design process, hoping that they may increase our understanding.

In this section, alternative generation and assessment phases in urban design will be discussed in further detail.

### *2.3.1 Alternative Generation in Conceptual Design Phase*

There are many different approaches to structuring the urban design process, and each of these attempts to contribute to our understanding of the complex design problem.

In his thesis, John Borrego (Borrego, 1968) proposed concept generation models as an attempt to describe the recurrent nature of urban design and the dynamics of its continuous design process, admitting that these models are not totally adequate, as they are not expressive of cyclical nature of design that may be simultaneously active along several fronts and may progress from general to specific or the other way.

Two models were proposed by Borrego, one shows the development of a single solution and another of multiple alternatives in series, which will be explained in detail in the following section. The use of models is paramount in the process, while designer's choice of the models depends on available resources (time, money, manpower, information, etc.).

2.3.1.1 Development of a Single Solution

**A. Single, Whole:** Solution is developed incrementally and sequentially then implemented (Figure 2.3).

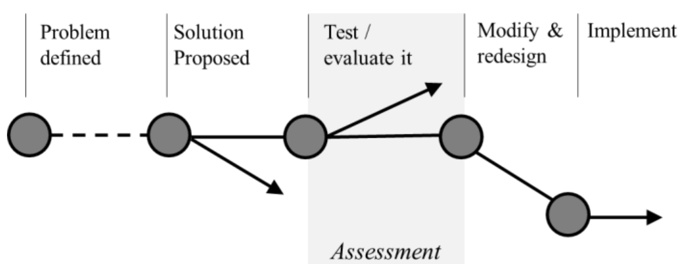



**Figure 2.3: Diagram of development of single, whole solution**

B. **Single, Fragmented:** Single solution developed by fragmenting the problem into its parts or sub problems (Figure 2.4).

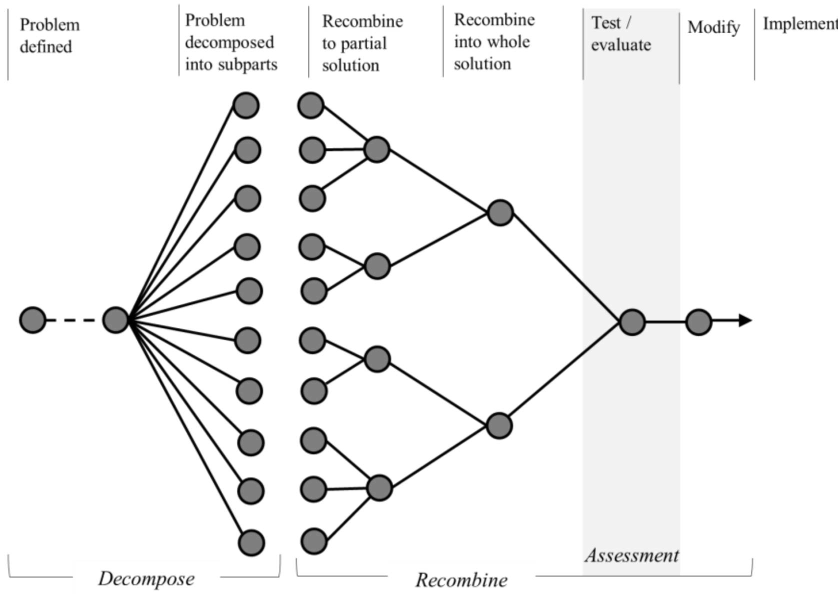



**Figure 2.4: Diagram of development of single, fragmented solution**

C. **Single, Recycled:** A single whole solution is developed but is expected to be rejected by the client. The designer recycles and another solution is attempted which may also fail. This recycling process is continued until an acceptable solution is reached. The client and the designer, through a process of trial and error attain an acceptable solution (Figure 2.5).

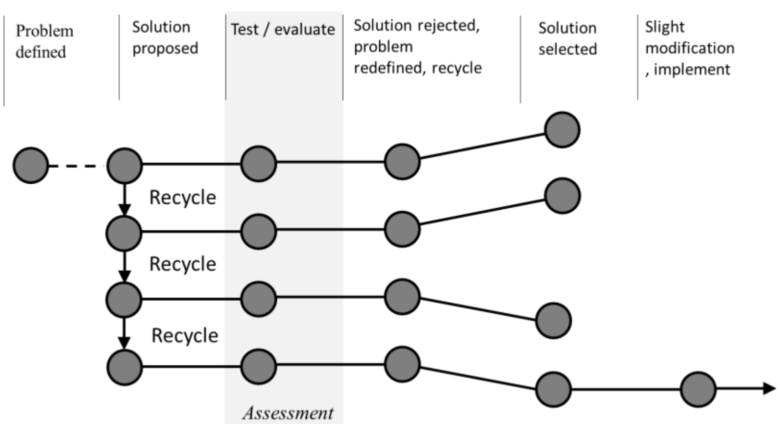



**Figure 2.5: Diagram of development of single, recycled solution**

2.3.1.2 Development of Multiple Alternative Solutions

**A. Competition:** Multiple whole solutions are generated initially by groups or individuals. A scheme is selected, modified and implemented (Figure 2.6).

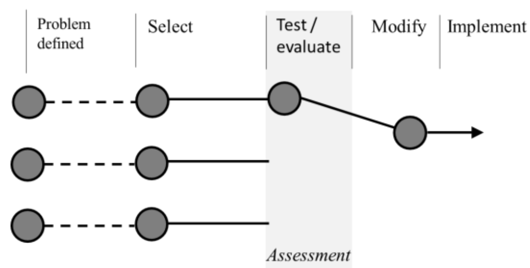



**Figure 2.6: Diagram of development of multiple competitive solutions**

**B. Multiple Alternative suggested initially:** Multiple whole alternatives are selected initially. These are then analyzed, recombined and a few are selected for final development and eventual selection. This is a process of initially expanding the solution realm, developing several alternatives and then converging on a solution (Figure 2.7).

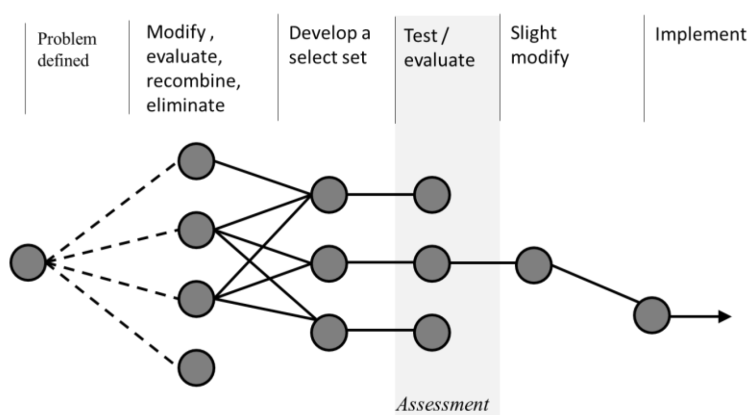



**Figure 2.7: Diagram of development of multiple alternative solutions**

One of recurrent steps in theses alternative generation methods is evaluation and assessment, which leads to modification in initially proposed alternatives. In the subsequent section, concept assessment is discussed in detail.

### *2.3.2 Alternative Assessment in Conceptual Design Phase*

In the Concept assessment phase, alternatives are evaluated and selected by identifying which best fulfills design requirements and objectives. Evaluation of design concepts is considered the most vital phase of product development due to its influence on all subsequent phases that define cost, quality and performance of the end-product.

The assessment strategies used in the early design stage of urban design heavily depend on designer's experience and rules of thumb, especially for performance measures that are difficult to compute in the early design stage with many unresolved hence uncertain design parameters, such as: urban energy consumption and microclimate properties as they require detailed input variables for their complex computation models. The models generate values for corresponding measures based on decided as well as undecided parameters which together form the set of urban characteristics that determines the performance of the proposed alternative.

Applying simulation tools directly to a specific urban fabric may get accurate results, however complexity and uniqueness of urban forms in the real world makes the findings less generalizable and useful for design guidelines and principles. Therefore, some scholars relied on simplified urban form archetype patterns to represent complex real urban fabric. The most commonly used simplified schemes are that of Martin and March's archetype urban patterns (Martin & March, 1972), where they extract six basic building types and their composition led to six generic urban forms (Figure 2.8). Martin and March's archetypical urban forms have been adopted extensively during the past three decades, because of their simple and repeatable characteristics that abstracts the complexities found in real urban sites. Example of such studies include thermal performance assessment if non-air conditioned buildings in context of hot-dry climate (Gupta, 1984), identifying key environmental characteristic and linking urban form descriptors to environmental performances (Steemers , et al., 1997), relation of building form and environmental performance in arid climate (Ratti, et al., 2003) and correlating density with built forms (Steadman, 2014). However, these studies are limited to singular performance measures, specific climate type and unrealistically simplified urban forms, making the application of these research findings as rules of thumb restricted to specific cases and not generalizable.

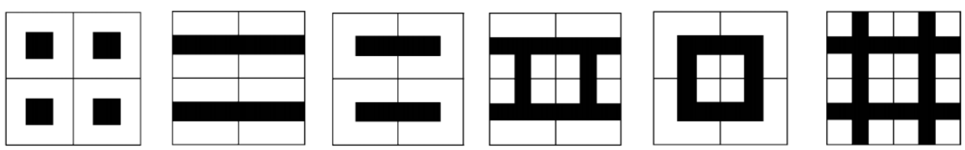


**Figure 2.8: Generic urban form, based on Martin and March archetype (Martin & March, 1972)**

In an urban context, the geometry of individual buildings alone becomes insufficient in capturing the influence of the urban environment. Therefore 'obstacle angle', which is defined as the obstruction height divided between the distance and target is used contextual parameter to represent surrounding urban context. Multiple studies established a general relation between simple geometric measures (obstruction angle) and shading effect on building energy performance (March & Martin 1972; K. Steemers 2003). Nevertheless, these relationships cannot be generalized comprehensively and used as design guidelines and principles for different climate zones and building types.

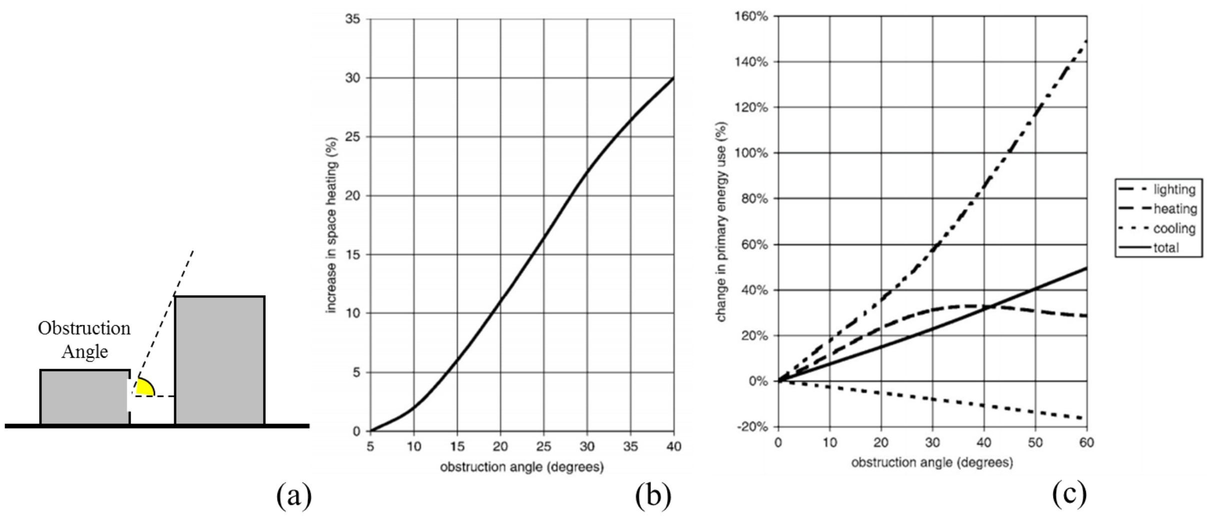



**Figure 2.9: (a) Obstruction angle, (b) Relation between obstruction angle and space heating for house (Martin & March, 1972)s, (c) Relation between obstruction angle and building energy use of offices (Steemers , et al., 1997)**

Urban fabric also has an influence on local weather and microclimate parameters depending on its scale. Urban canyon is the scale, where interaction between buildings and environment happen. Urban canyon is referred to as the basic urban surface unit consisting of walls, roofs and ground between two adjacent buildings. Multiple studies correlate geometric measures of urban canyon to different climatic measures (Oke, 1987; Erell, et al., 2012), others use detailed model approach to represent real urban environment (Emmanuel & Fernando, 2007). However, because of the uniqueness and complexity of urban settings, the findings of these studies are case dependent, hence correlation between urban geometry and climate can seldom be generalized.

There have been multiple attempts to link ‘urban density’ to measurable performance dimensions with the aim to determine ‘appropriate’ densities. Performances in these cases are viewed as extensions of the objective character of density into the physical realm of urban fabric. To regard these as performance is questionable from a functional perspective, and it would be better to regard them as aggregate properties of urban form that serve as proxies to true performance. Pont and Haupt (2009) emphasized the importance of defining the relationship between urban density and performance, and the evaluation of these performances. Urban density is represented using ‘*spacematrix*’ (Figure 2.10, a), which defines density as a multi-variable property and establish a correlation between density and built mass (urban form). *Spacematrix* uses the following measures: floor space index (FSI), ground space index (GSI), and network density (N). These measures are represented in a three-dimensional diagram, the *spacematrix*. Measures such as open space ratio (OSR) or spaciousness, the average number of floors or layers (L) and the size of urban block (w) can be derived from that (Pont & Olsson, 2017). It is also stressed that indicators derived through said density must be treated as abstract approximations and used with knowledge of its indicative and literal character. Those derived indicators are useful for comparisons and for gauging trends, not as descriptions of individual components (Pont & Haupt, 2009). Three performance examples were explored in Pont and Haupt’s work: parking, daylight access and urbanity (Figure 2.10), in order to demonstrate how density can be associated with true performance indicators.

Although *spacematrix* is works as a general regulatory guideline, one of the major of limitations of deriving performance indicators through *spacematrix*, is that it is best applicable to static performance, hence it is difficult to apply it to performance measures that change with time and location (such as thermal comfort and energy consumption). In addition to that, it deals with fully defined parameters, and it will be hard to incorporate the role of design uncertainty in this technique.

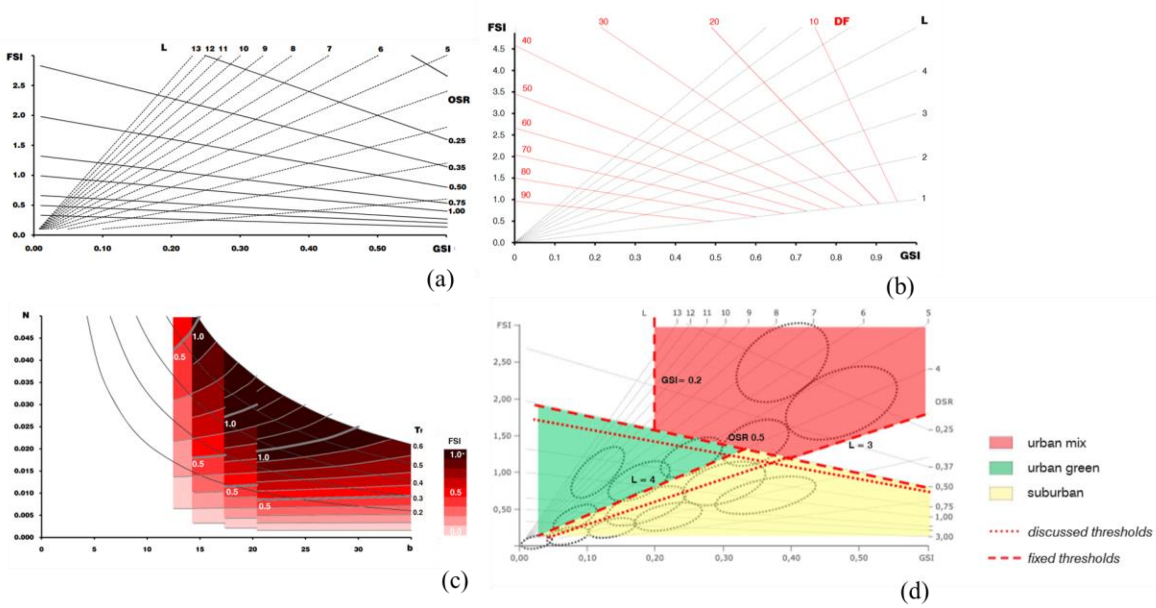


**Figure 2.10: (a) *Spacematrix*, (b) Spacematrix with gradients of daylight performance index in the interior, (c) FSI threshold values for different parking capacity, (d) Living environments, zones in *spacemate* and scale level of assessment (Pont & Haupt, 2009).**

There have been multiple attempts to create support tools and metrics to evaluate the qualitative aspect of city streets, parks, squares and other outdoor shared spaces. Lynch, in The Image of the City suggested that public space is used as means of creating urban identity. The physical or spatial qualities of a space play a large part in creating a space's identity. People recognize and use spaces based on these qualities and these qualities also help to form and reinforce emotional connection as the cultural root (Lynch, 1960). One of the greatest challenges in evaluating public space is that much of the data in the design process has a non-mathematical nature and it is difficult to identify the parameters of urban form that are quantifiable (Koltsova, et al., 2017).

The concept assessment phase needs tools and platforms that can not only adapt to versatility of the urban fabric design, but also take design uncertainties at the early design stage into consideration. Assessment tools need to be rapid and highly responsive to design iterations for them to be applicable at early design stage, when concepts and design parameters keep changing.

### *2.3.3 Alternative Selection in the Conceptual Design Phase*

Design decisions are frequently made based on insufficient data; moreover, these same decisions commit designers to future actions. The decisions keep getting reconsidered under the light of newly attained knowledge, more often than not making designers return to earlier stages of the process.

Pugh (Pugh, 1996) states that selection of best concept is one of the most difficult, sensitive and critical problems in design. It is significant that the best initial concepts are selected early, as they determine the direction of the design embodiment stage. Salonen and Perttula (Salonen & Perttula, 2005) point out the following characteristics of concept selection, which makes decision making complexity more apparent:

1. Select the most promising concept for further development in the early design stage.
2. Recognize the existence of unknowns and uncertainties both in the concepts and criteria.
3. Involve several decision makers with varying expertise and preferences.
4. Know the impact of selected concepts on subsequent steps of the design process.

Designers are faced with the task of identifying design requirements and subsequently evaluating all generated concepts accurately. Based on which underlying principle is used, concept sections methods (CSM) are classified in the following categories (Kremer, 2008):

1. ***CSM based on decision metrics (Pugh Matrix):*** Pugh (Pugh, 1995; Pugh, 1996; Pugh, 1991) developed a graphical method which utilizes a matrix with columns (concepts) and rows (decision criteria). One of the concepts is chosen as datum for comparing other concepts against it. A concept is assigned "+" if it scores more than datum "-" if less. These "+" and "- "are summed up for each concept and lower scoring concepts are removed, this is repeated iteratively until a decision is reached. This graphical method is simple and fast, it also provides an insight to the concepts that are decidedly better than the others. However, this method does not allow for coupled decisions and uncertainty cannot be modelled in this procedure (Figure 2.11, a).
2. ***CSM based on analytic hierarchy process (AHP):*** Saaty (1980, 1994) (Saaty, 1980; Saaty, 1994) developed AHP as decision making tool involving multiple attributes. The problem is broken down into hierarchies with design goal being topmost hierarchy, followed by sub-criteria and finally the alternatives or concepts in the bottom hierarchy. In order to achieve the goal, pairwise comparisons between criteria is carried out to determine relative importance of each criteria and based on these comparisons, overall selection is made. Although AHP allows for useful comparison between criteria and alternatives, as the number of criteria and alternatives increase, the calculations become increasingly

complex. Also, AHP does not allow for coupled decisions nor does it accommodate uncertainty (Figure 2.11, b). Moreover, as Hazelrigg (2012) points out, the method is theoretically flawed.

3. ***CSM based on uncertainty modelling:*** Due to the incomplete and imprecise information in early design, it is difficult to assess the relative importance of attributes, relationships between attributes and resulting performance and estimated cost. In the following general methods, uncertainty can be incorporated into decision-making (Figure 2.11, d).
    a. Non-classical mathematics
    b. Probabilistic mathematics
    c. Fuzzy clustering

5. ***CSM based on decision theory/economic models:*** In this method, concepts are evaluated using a utility function. Utility theory is a normative approach for decision making that utilizes a rational evaluation of alternatives based on three components: options, expectations and value. Decisions are made based on alternatives with highest expected utility (Krishnamurty, 2006). Forming a decision maker specific utility function that can be used for concept selection is a difficult task that involves carefully crafted elicitation of value statements from stakeholders, and it is generally hard to accommodate coupled decisions.

6. ***CSM based on optimization concepts:*** One of the most powerful means for resolving multiple criteria with their own objectives is multi-objective optimization. Numeric techniques are used to identify optimal solutions, and in case of multi-objective optimization over a set of design parameters, one can

inspect an infinite number of solutions and find those that are candidate optimal solutions referred to as "Pareto optimal solutions" (Mattson & Messac, 2005). If grouped together these candidates lie on the so-called Pareto front. However, this approach does not incorporate uncertainty, nor does it account for coupling among design decisions (Figure 2.11, c).

7. ***CSM based on heuristics:*** Prevailing CSMs use qualitative techniques to select a few designs from multiple possible options, to perform a detailed analysis on each option to determine its performance and characteristics. By parameterizing the design options the decision problem boils down to finding an optimal point in a typically large option space. To tackle this large search space, genetic algorithms (GA) have become popular.  They use a form of stochastic search along paths that mimic nature's evolutionary process and uses nature's gene replication theory to find fitter designs, i.e. with improved and ultimately best performance. In general, the heuristics do not support explicit uncertainty (Figure 2.11, e).

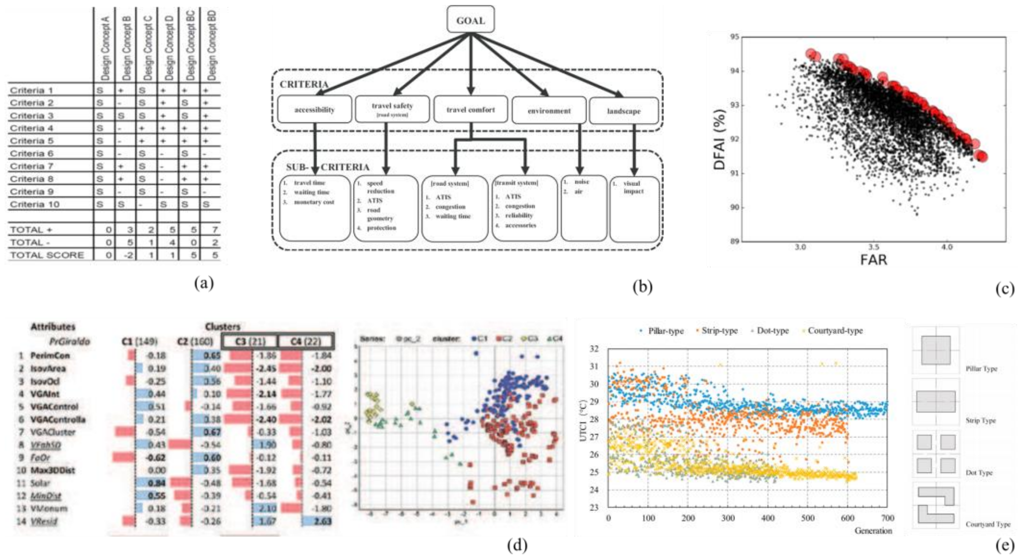


**Figure 2.11: Concept selection methods applied on urban scale (a) Example of a completed Pugh Matrix, (b) AHP application in transportation planning (de Luca, 2014), (c) Optimization generated 500 design variants with 51 on *Pareto-front* (Chen & Norford, 2017), (d) Example of a clustering for open space prototype evaluation (Lopes, et al., 2017), (e) Comparison of variation of four basic block types in outdoor average thermal comfort (UTCI) in July (Yeh, 2002).**

Different methods for design decision-making can result in different final solutions (Yeh, 2002). Thus, selecting a suitable decision-making method from a group of available methods is itself a critical decision (Hazelrigg, 2012). In the latter source a good treatment of the systemic role of uncertainties in design decisions can be found, which is summarized below.

All decision making is considered optimization, as the decision maker is presented with alternatives to choose from, and only one choice is allowed. This choice must come from set of available alternatives, the decision maker holds beliefs about the outcome of each alternative and has a preference order on the outcomes. Optimization is all about finding that alternative whose outcome is most preferred. In the mathematical process of optimization, we first identify the set of available alternatives, then outcomes of the alternatives are computed and assigned a real scalar value to each, from which a preferred choice is made by identifying the alternative with highest outcome value. This is true for deterministic decision making; however outcomes of decisions are always in the future, hence they can never be known with both precision and certainty at the time of decision (Hazelrigg, 2012).

The issue with classical (deterministic) optimization is the fact that it assumes that we know the future with precision and certainty, which is not realistic. The goal of decision theory is to relax the condition that the future must be known with precision and certainty. There are three parts in a decision: the alternatives from which a choice is made, the decision maker’s beliefs about the outcome of each choice and a preference ordering on the outcomes. In classical optimization, the choices and preferences are deterministic.

Decision theory is a framework for thinking logically about choices in the presence of uncertainty on outcomes of choices. Hence, the only difference between deterministic optimization and decision theory is that the decision theory allows for uncertainty in outcomes. Uncertainty in outcomes means that choices cannot be assigned a real scalar value or mapped directly as a point; they must be mapped as probability distributions.

Design decisions never deal with one single performance aspect; inherently successful design is one that can satisfy many performance requirements. This implies that multiple stakeholders are engaged in the dialogue, and that performance verification deals with many performance criteria simultaneously. The primary objective of decision making is to recognize the trade-offs between different criteria.

Although optimization techniques seek an optimal solution by minimizing or maximizing a certain objective function, implementing them at the early design stage is impractical. This is because: (1) In the urban design process, we are not trying to find the "most optimal solution", rather the aim is to identify the design options that fulfill performance requirements. (2) Optimization application lacks the ability to help designers in a complex design process where it is important to understand the relationship of different design parameters and their impact on performance measures. (3) In urban design practice decisions are made iteratively, hence implementing optimization at every decision stage is not feasible.

The early design stage -which is the focus of this thesis- is characterized by considerably more uncertainty as compared to subsequent design stages. For an alternative selection method to be applicable at this stage, it needs to be able to deal with design uncertainties, which will be discussed in the following section.

## 2.4 Uncertainties

### *2.4.1 Uncertainty Definition*

Uncertainty refers to our inability to predict the future with both precision and certainty, whereas risk is the variability in the objective function for a decision, which can be mapped to positive (gains) or negative (losses) consequences. Risk refers to the potential (expressed as a probability) revenue or damage that the outcome of a decision will result in. A popular definition of risk reflects this as follows:

**Risk = Probability (Event) * Damage (Event)**

Simulation platforms facilitate the assessment of the design response to certain conditions by means of a computer model. It is an instrument, which is exceptionally suitable to answer “what if”-type questions. This type of questions typically arise in a decision making context, where the consequence of various alternative courses of action are to be assessed (de Wit & Augenbroe, 2001).

Commonly these consequences can only be estimated with some degree of uncertainty. There are many sources of this uncertainty, the first of which is the lack of knowledge about certain physical parameters in the design representation, notably those that describe physical properties of building components and systems. We generally group them; in the category ‘**design parameter uncertainty (P)**’. This lack of knowledge is mostly related to so-called realization uncertainty, i.e. the uncertainty about how an actual design specification is realized as the built object. Even if the design is realized and the physical object exist, there is a limit to how many design (now “actual”) parameters can be observed or extracted accurately.

In addition to our lack of knowledge about physical parameters, there are several external factors imposed on the building, which drive the predicted response and may not be precisely identified, this is generally categorized as ‘**scenario uncertainty (S)**’. Finally, there is uncertainty that is systemic to the prediction itself i.e. as the result of our inability to model the physical world in all its complexity correctly. It is in fact necessary to introduce simplifications in computer simulation models, this imperfect representation of reality in simulation model that lead to uncertainty in the outcome is categorized as "**model-form uncertainty (MF)**' (Malkawi & Augenbroe , 2003). In short, the three categories each form their own contribution to the gap that exists between our model predictions and reality, or in symbolic form:

$$\textbf{Outcome}_{\textbf{Model}} \textbf{ - Outcome}_{\textbf{Reality}} \textbf{ = P + S + MF}$$

Many studies have demonstrated the significant role of uncertainty analysis in the context of building design and retrofit decisions. Heo Augenbroe and Choudhary (2015) evaluated the uncertainty in energy retrofit decision making in the context of performance-based contracts (Hu & Augenbroe, 2012). De Wit and Augenbroe (De Wit & Augenbroe, 2002) evaluated probability distribution of unmet thermal comfort hours to determine the need of mechanical cooling systems.

This thesis does not focus on accurate prediction of the outcomes of the realized design. Indeed, in the early design stage when many details about the realization are missing, this would be a futile exercise. Rather this thesis focuses on the comparison between alternatives during this early stage. For this type of comparative analysis, the uncertainties identified above play no or only a minor role. We focus therefore on the role of a higher-level uncertainty, i.e. '**design parameter uncertainty**' or in short "design uncertainty" which inclusively can be identified as the unknown values of undecided design parameters. These represent uncertainty in the evolution of design, associated with parameters on which a decision has not yet been made. Other modeling uncertainties addressed earlier as P, S and MF become important at the later stages, i.e. when inspecting the gap between performance predictions (for the final fully developed design case) and the actual performance that one can expect after the realization. The latter is not in the scope of comparative design proposal analysis and will therefore not be considered.

Undecided design parameter uncertainty quantifies the lack of knowledge in aspects of design that have not yet been decided upon but can possibly be represented by specific probability distributions that show the probability that a certain value will eventually be decided upon. As we will see later, the choice of the range of possible values and their probability of occurring in the final design is a vital input in the comparative analysis. Undecided parameters are obviously of particular importance in early design decisions when final form of the design and its evolution process is largely unknown. Making a rational choice between competing design proposals (each represented by set of design parameters) has to respect the fact that some parameters that are relevant to the performance assessment are still unknown. Our decision making should thus account for the fact that we don't know the values of these parameters as their determination happens in a later stage of design. Uncertainty in undecided parameter is particularly high in the early design phase, making performance-based decision making with confidence particularly challenging at this stage. Taking this type of uncertainty into account in early design, can help in identifying promising design alternatives and implicitly show how future decisions can influence a positive or negative performance outcome of a design proposal under consideration.

Analysis of uncertainty and its impact on the designer's confidence in decision making is essential when exploring the design space and guiding the evolution of a design through decision-making (De Wit & Augenbroe, 2002). Rezaee, Brown, Augenbroe and

Kim (Rezaee, et al., 2014) integrated energy tools in CAD for performance-based decision making in early design. The latter study, and most uncertainty analysis studies for that matter have focused on individual buildings. Hardly any attention has been given to this filed when designing at the urban scale. This work explicitly focuses on performance-based decision making in early design taking into consideration the uncertainty in undecided design parameters.

### *2.4.2 Incorporating Uncertainties in the Design Process*

In the practical application of simulation platforms, explicit appraisal of uncertainty is the exception rather than the rule and most decisions are based on single-valued estimates. If we consider simulation platform as an instrument, which aims to contribute to decision makers' understanding and overview of the decision-problem, it seems natural that uncertainties get accessed and communicated. Hence, the lack of concern for uncertainty in the current practical application is surprising.

Lack of focus on uncertainty in current practice is quite natural, as most available design assessment tools facilitate modeling and simulation of complex designs but provide no support to explore and quantify uncertainty in the assessment. Also, selectively refining or simplifying model aspects are limited in most simulation environments. Currently there is no concern is given to the question how quantitative uncertainty can be used to better-inform a design decision.

For incorporating uncertainty in design practice, the first stage is crude, for each parameter existing information is used to extract probability distribution along with finding statistical dependencies between parameters. Plausible ranges of these parameters and their interpretation in terms of probability is then assigned. There is no general rule on how to quantify these parameter uncertainties, it can be extracted from literature, experiments, model calculations, rules of thumb or experience. The focus is not only on a “best” estimate, but also on the uncertainty range. To rigorously apply this thinking to the quantification of design uncertainty is hard and largely unexplored. Rezaee et al (2015) present a method that is based on inverse identification based on information gathered for large swaths of buildings. This method would be applicable to the urban situation after a thorough data analysis of many existing urban designs. As this data is not available at this time, this study will rely solely on the expertise of the urban modeler. This will be further explored as part of the case studies in Chapters 4 and 5.

Once the design uncertainty represented in probability distributions of model parameters, the resulting uncertainty in the model output is generated. This process is referred to as the propagation of the uncertainty. For selecting an appropriate propagation technique, the first question is: what should the propagation model produce? Commonly it is sufficient to only calculate specific aspects of probability distribution, such as mean and standard deviation or the probability that a particular value is exceeded. Different techniques can be applied depending on required knowledge of the distribution of the propagated “quantity of interest” or QoI. A second criterion for selecting the propagation technique is the economy of the method, in terms of number of samples required to obtain sufficiently accurate results for the distribution of the QoI. For obtaining reliable results, it is important to verify whether parameter uncertainty assumptions hold for the model in hand. For practical use, an additional aspect of interest is commonly the ease and flexibility of applying the method to the simulation tool (Malkawi & Augenbroe , 2003).

## 2.5 Conclusion

The early design stage is characterized by its iterative nature consisting of concept generation, concept assessment and selection that, we argue, implies decision-making under uncertainty. Hence, the methods and tools applied in this stage should consider the iterative, complex and to some degree random outcomes of the design process. In the beginning, simple crude models are used for assessing the performance, but as the design proceeds these crude models are typically replaced by detailed complex models, which require more time to generate output, hence due to time limitation, the number of design alternatives that go through this assessment is reduced. There is a clear need to develop robust and simple methods, incorporating uncertainty analysis, to assist the designer in generating, assessing and selecting promising design concepts.

The next chapter will explore current methods and tools used in performance-based urban design and evaluate if these approaches have the required characteristics to fit our early design focus.

# CHAPTER 3. REVIEW OF CURRENT APPROACHES IN PERFORMANCE-BASED URBAN DESIGN

This section will briefly overview the current approaches in performance-based urban design in the early stage, and will address the following questions:

a) What approach does the current design workflow use for *concept generation*?
b) What models and tools are currently used for *performance assessment* in early design?
c) How are unknowns (*undecided parameters*) accounted for in performance evaluation in early design?

## 3.1 Concept Generation in Urban Design

Currently designers generate concepts based on their experience and tend to disregard many by not exploring their potential in a meaningful way. This happens because performance-assessment in current approaches are used to answer one of the following questions:

• "Does the proposed design satisfy desired objectives?"

• "Which design has better performance as measured by defined performance indicators?" Quantifying performance criteria is used to rank design alternatives through comparative analysis.

Hence, the analysis tools focus on these two questions by evaluating and ranking a limited number of generated alternatives mostly based from designer's experience. Prevailing approaches therefore don't help the designers during divergence, and instead are used for performance analysis during convergence. The question that needs to be asked instead is:

• What design has greater potential to satisfy defined performance objectives at the final stage?

This approach of assessing the potential of alternatives in achieving certain objectives, has more impact in the divergent phase as we can evaluate the potential of design alternatives at an early design stage.

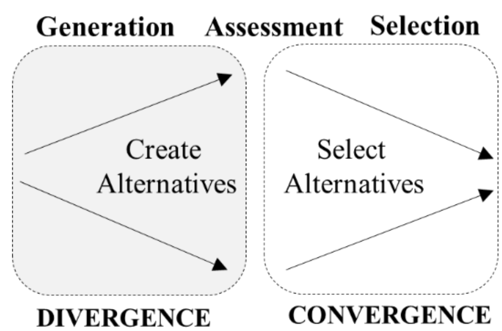



**Figure 3.1: Divergent phase of Conceptual Design Process**

Designers seek to fulfill their performance requirements without a clear framework for design exploration and assessment. It is important to understand that formulating performance requirements and carrying out assessments are not sufficient guarantee as the end result depends on both the decision-making approach as well as when to make those decisions, i.e. the process workflow (Augenbroe, 2019).

A common trap that many researchers fall into is treating the urban design as an object placement problem without considering the design process that leads to this placement and solving it as a massing optimization problem with specific performance requirements. This way of portraying an urban design problem might result in the most optimal object placement that achieves maximum or minimum value of a set of defined performance measure, but this method cannot be applied to real world urban design process as it oversimplifies it and disregards the entire urban design workflow process.

On one hand the urban design process is over-simplified as a mere massing problem, where the aim is to find the most ‘optimal’ massing placement to either maximize or minimize an objective function (Figure 3.2), such as maximizing daylight availability (Agarwal, et al., 2017) or minimizing solar radiation ( Vermeulen, et al., 2015). Whereas on the other hand it could be treated as a complex computing problem, where the entire design process is automated to generate ‘optimized’ urban layouts giving little room for designer’s creativity to emerge. The process does save time spent in the divergence phase, but it also generates a much larger design space than is necessary to address the given problem. An example of such approach can be found in DeCodingSpaces Toolbox (Figure 3.3), in which a spatial synthesis process is automated and an evolutionary multi-criteria optimization algorithm is used for developing a solution space for the street network of an urban block (Miao, et al., 2017).

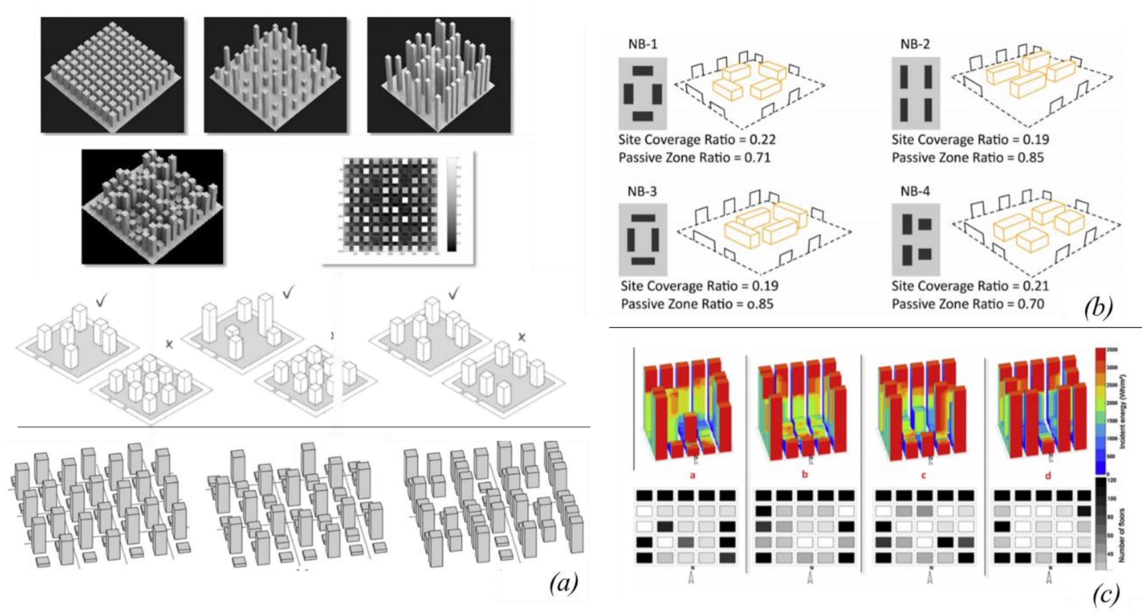



**Figure 3.2: Examples of urban area generation (a) Urban setting optimization based on daylight availability (Izzo, 2017), (b) Building placement optimization based on daylight performance (Agarwal, et al., 2017), (c) Urban height optimization based on solar radiation ( Vermeulen, et al., 2015).**

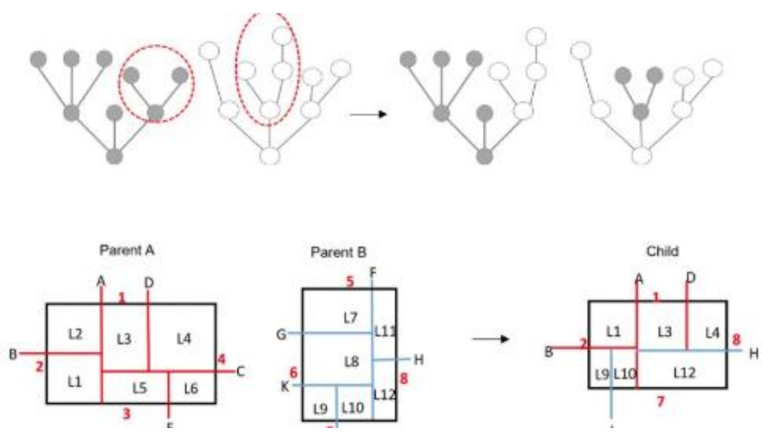



**Figure 3.3: Examples of block subdivision "cognitive design computing" (Miao, et al., 2017).**

The prevailing performance-based approaches don't help the designers in generating alternatives. They are primarily focused on the performance assessment, which does not impact early design decisions during concept generation. In order to help the designer to make risk-conscious decisions in the early phase of design, we need to provide performance analyses at the early stage when many of the parameters have not been decided upon rather than late in the design process when the majority of the parameters are decided but any detailed assessment of performance will not impact the choice of design alternatives that could have been considered earlier in the process.

### 3.2 Performance Analysis Tools and Methods in Urban Design

Performance assessment phase is mainly focused on analyzing and selecting designs that help in achieving a set of desired performances outcomes (expressed as desired values of a set of performance measures). Multiple urban analysis methods and tools exist with different resolutions, these tools help in understanding the relationship between different parameters and the performance measures (Table 3.1). The adequacy of these methods and tools highly depends on the design stage. Approaches that don't need a high number of parameters, are used in early design stages, whereas methods and tools that need detailed design information are used in later design stages when most parameters are decided upon and these analysis lead to more accurate results as compared to simplified assessments and experience-based methods. The latter will be explained below.

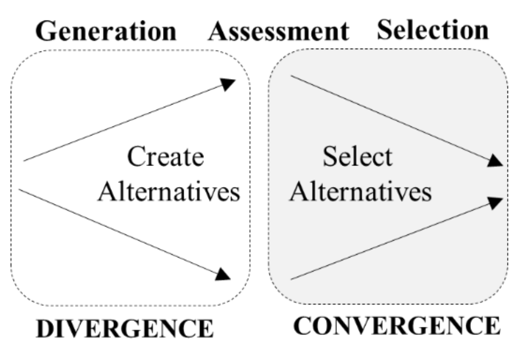



**Figure 3.4: Convergent phase of the Conceptual Design Process**

During early design, when most of the parameters are unknown, designers rely on their experience in the form of ‘qualitative design guidelines’. Designers who rely on their experience, derive their guidance from “rules of thumb”. These methods attempt to connect to observations from the real world with scientific principles, however generalizing these simple rules is not always feasible, nor is it feasible to collect sufficient rules for making an informed decision.

As parameters get defined in design development, physics-based models are used for performance assessment, examples of such methods and tools are: SunTool, which is used for environmental modeling of urban neighborhoods (Robinson, et al., 2007), UMI, an urban modeling design platform used to carry out operational energy assessment, sustainable transportation choices, daylight and outdoor comfort at the neighborhood and city level (Reinhart, et al., 2013), Space Syntax (Hillier & Hanson, 1993), a network analysis tool used for evaluating connectivity and relation of urban networks, and ENVI-met, an urban microclimate analysis tool (Bruce, 2007). After design completion, in the post evaluation stage, empirical studies and real time data models are used for representing observed behavior for retrofitting purposes. In empirical studies, human and environmental interaction with urban space are used to establish an empirical correlation between different parameters (Koltsova, et al., 2017), whereas real time data models, such as CityBES (Chen, et al., 2017) act as a platform for urban planners and city energy managers for energy retrofit planning and other interventions (Figure 3.5).

**Table 3.1: Performance evaluation approaches in Urban Design**

| | Approach | Method | Design Phase | Example |
|---|---|---|---|---|
| Low Resolution | Experience | Qualitative design guidelines | Early Design | A Pattern Language (Alexander, C.1977)<br>Livable Cities (Gehl, 1987), |
| | | Rules of thumb | | Spacematrix (Berghauser-Pont and Haupt, 2010),<br>Transit Oriented Development,<br>March and Steadman, 1974<br>Brown and DeKay, 2000 |
| High Resolution | Simulation | Physics Based Models | Design Development | Sun Tool (Robinson, et al. 2007),<br>UMI (Reinhart, et al. 2013),<br>Space Syntax (Hillier and Hanson, 1987),<br>ENVI-met (1993) |
| | Real Data | Empirical Studies -Case Based | Post Evaluation | Koltsova, Tuncer, & Schmitt, Stratification of Public Spaces based on Qualitative Attribute Measurement, 2017 |
| | | Real-time data models | | SimStadt (Eicker, et al. 2012),<br>CityBES (Chen, Hong and Piette 2017) |

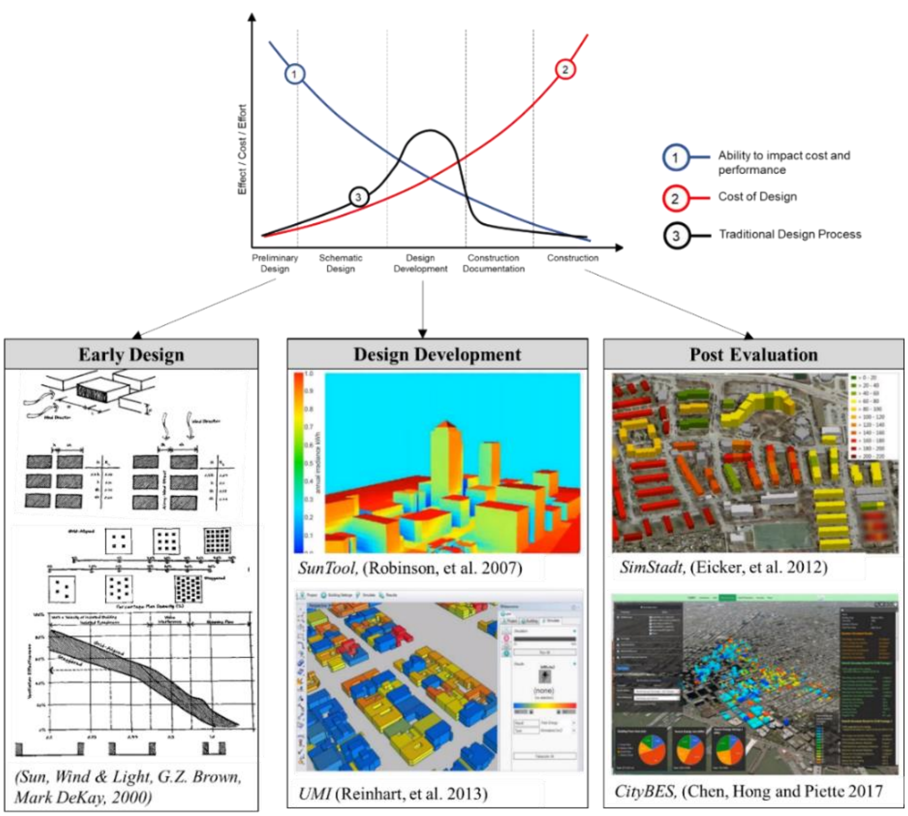



**Figure 3.5: Urban Simulation Tools at different design stages**

One of the key elements of every decision is ‘preference’, a decision-maker needs to establish preference over the possible outcomes of various available choices. An expression of preference is needed in a performance-based design, as without it, a decision maker would have no means of affecting a decision and there is no mechanism to select one alternative over another (Hazelrigg, 2012). In many cases preferences are objectified in the form of statements that compare outcomes of alternatives to predefined desired value and choose the one that has the highest score.

There latter explains the need to move in the direction of performance-based urban design, which needs performance-based statements of requirements and a transparent process that if not guarantee, would at least increase the chances of their fulfilment. This essentially requires the support of the dialogue between stakeholders and designers. Two dialogues are of importance:

1. **Dialogue 1 (Decision-maker):** What is the intention of use of urban fabric that is being designed (Function)

2. **Dialogue 2 (Designer):** What are the criteria to define and associated measures to quantify the performance of urban fabric (Performance Measure)?

The functional intention of designing urban fabric plays a major role in determining what type of performance (defined as a set of criteria) is expected by stakeholders and decision makers and their fulfilment by designers. The disparity between expectation and fulfilment of desired performance are rampant throughout the design process.

The current design process lacks a transparency with respect to objectively quantifiable expressions of requirements and lacks proper assessment tools to ascertain that expectations have been fulfilled by a proposed design. Traditionally the mentioned dialogue has been cast in prescriptive terms, by prescribing physical aspects of the solution rather than making statements about the expected performance of the solution.

There is an obvious failure to add quantified elements into dialogues, largely due to apparent cultural resistance towards quantification of design performance, mainly because of the strong believe that urban performance cannot be measured. The reasoning is that design value can be interpreted based on qualitative judgments, which in turn rely on the unpredictable manifestation of the space in its future and changing context of use. There is no disagreement that these judgments will always be biased by the ‘value system’ of the person who measures and this invariably leads to rather subjective measures of urban “quality” which are loosely defined as ‘a set of characteristics that are perceived to contribute to value’. However, this approach is no longer acceptable, and it can be argued that many performance aspects of the urban space can and should be objectively measurable. The performance characteristics that are most amenable to an objective statement are those that relate to functions that the urban space is designed to perform. Instead of relying on subjective ‘quality’, a more objective ‘utility’ should be introduced, where the ‘utility’ represents some client-relevant aggregation of objectively measurable performance characteristics.

To compare the performance of different urban fabric options, objectively quantifiable measures are needed, which can be implemented as a set of uniquely defined criteria, each of which is associated with a ‘performance measures’ that provide quantitative assessments of how well an urban fabric achieves a decision maker’s performance objective. A ‘performance measure’ is defined such that it allows the evaluator to understand how multiple urban attributes interact to produce given level of urban fabric performance. A performance measure can be used to state expectations as well as quantify actual performance fulfilment.

In today's performance analysis world, simulation has become an essential component and a variety of simulation software and tools have thus been introduced for different urban performance analyses and evaluations. For implementing these models in early design, reduced order models are suitable as they require a less detailed description, i.e. fewer inputs by relying on normative assessment. The latter relates to the application of predefined (hence the term normative) rules for model construction and external input selection. In simple terms, a normative approach compares different solutions by subjecting them to a simple experiment that is not meant to represent reality but is adequate to reveal which solution will perform better in reality. The verification that a proposed normative assessment achieves that goal is typically done by comparing the outcome of the normative method with a large set of actual realizations and use of high-fidelity tools. An example can be found in (Kim and Augenbroe, 2013). The main benefit of normative assessment is that it can be done with fewer inputs and mostly low fidelity computational models, typically referred to as reduced order models. The main goal of using reduced-order models is not necessarily the accurate prediction of actual future performance, rather an accurate comparison of design alternatives and orderly ranking of different options (Augenbroe, 2019). In addition to that, this enables rapid –if coarse- evaluation of the factors that impact the performance measure. Using high fidelity tools in an early stage raises the fundamental concern that the way they deal with undecided parameters is to choose default values without accounting for the fact that they are unknown and could eventually take one of a range of plausible values. This obviously poses a source of uncertainty that is ignored in current approaches, and their deterministic outcomes could therefore be misleading in the selection of the best design option.

### 3.3 Design Uncertainty in Comparative Analysis and Alternative Selection

In this section urban energy performance of two urban design alternatives is estimated in a specific design decision scenario under consideration of design uncertainty. An alternative is selected based on sufficient confidence that it will in result in a most preferred outcome. Different decision situations are considered, in which a design decision (or more specifically a choice among competing alternatives) is to be made based on performance predictions of the available alternatives in the specific settings. Alternative selections thus decide between alternatives identified by their design parameters, which at any decision point can be divided into decided parameters $P_{dec}$ , which include parameters that have been decided and have determined values and undecided parameters $P_{undec}$ , consisting of design parameters that have not yet been decided upon, hence are uncertain. The undecided parameters contain a further subset denoted as $P_{todec}$, which is identified as the parameter set to be decided upon at the certain decision point. At each decision point, there is set of alternatives to choose from, and these alternatives are compared based on the set of outcomes determined by simulations models.

For this section, different case studies were chosen with different outcome preference. In addition to that, only two alternatives, A and B are considered as viable alternative at the decision points to simplify the treatment.

In current deterministic approaches, the aim is to investigate: “Is alternative A better than alternative B?” On the other hand, the question arising in probabilistic approach is: “Are we confident that alternative A will be better than alternative B once the design is complete and all parameters are determined?” Since the proposed probabilistic approach incorporates uncertainty, we need to predict the outcome in the form of a probability distribution which incorporates the propagated uncertainty. Consequently, the outcomes of each alternative will be represented by a probability distribution.

In case study 1 (Figure 3.6), the probabilistic and deterministic approaches are compared. The following treatment serves primarily as an illustration. By comparing the outcome of both approaches, it is evident that the deterministic approach provides a single value performance output, whereas the probabilistic approach shows the range of outcomes, i.e. all possible outcomes based on the possible value of undecided parameter, within given ranges. Deciding based on deterministic outcomes might limit a decision maker’s foresight, as he is replacing undecided parameters with determined values (often heuristically chosen default values), which might change as design develops. In the deterministic approach the hidden assumption is that these future changes of default values do not alter the favorability of one alternative over the other. In example 1 (Figure 3.6-b), alternative A has the higher performance and is thus favored over alternative B.

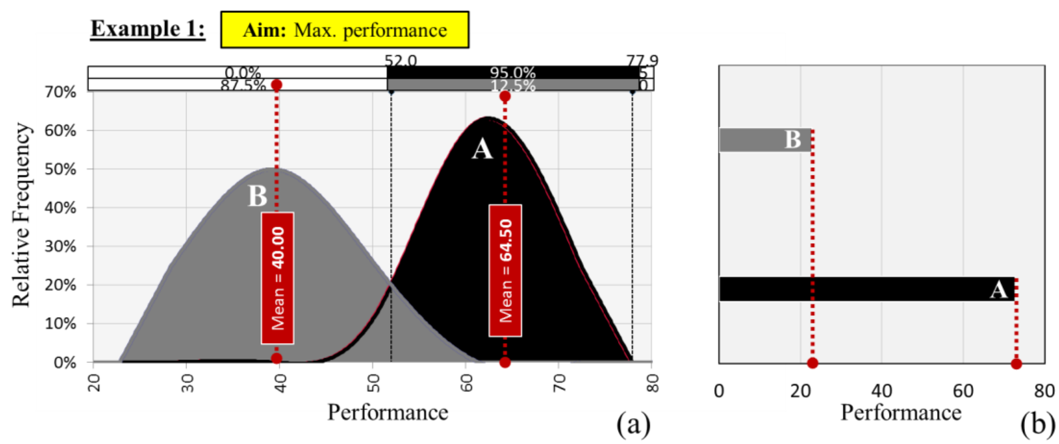



**Figure 3.6: Comparison between: (a) Uncertain design assessment, (b) Deterministic design assessment**

One of the most common ways of comparing probability distribution is by comparing the means of these distributions (Figure 3.6-a). Alternative A has mean 64.5 and alternative B has mean 40, and since the aim is to choose alternative with higher performance value, alternative A is clear choice. Comparing the means is obvious first criterion, but is not sufficient to make a decision confidently, hence we need to rely on an additional criterion for making a decision with more confidence.

One such method for comparing the two alternatives is by computing the relative difference between the two samples with common parameter values. The aim is to verify the chance of one alternative being better than the other by, say 10% or more. We denote PRD for probability of relative difference, defined as follows:

$$PRD = Pr[\Delta(A,B,M_j) \geq \phi] = Pr\left[\frac{Q_A - Q_B}{Q_A} \geq \phi\right] \geq \psi \qquad (1)$$

Here, Pr […] denotes probability of what is in the brackets, determined from histograms computed from the propagation of uncertainties in $P_{undec}$ through a simulation model $M_j$.

The variable ϕ is a decision maker's preference related to the relative difference between alternatives A and B, which is the chance that one alternative is indeed better than another by at least ϕ, as per outcome estimation using model $M_j$. The probability that is true can be regarded as the confidence and is denoted by ψ. It represents the confidence level that the outcomes estimated by model $M_j$, will be better by ϕ for one alternative over the other at the end of the design process. In example 2, PRD is calculated from the two outcome distributions (Figure 3.7-a) and plotted in Figure 3.7-b. Alternative A turns out to be 10% better than alternative B with a probability of 63.2% (Figure 3.7-b). In this case alternative A could be chosen over alternative B with 63.2% confidence level that A is at least 10% better than B. As per equation 1:

$$\text{PRD} = \Pr(A > B = 10\%) = \Pr(A > 1.1B) = 63.2\%$$

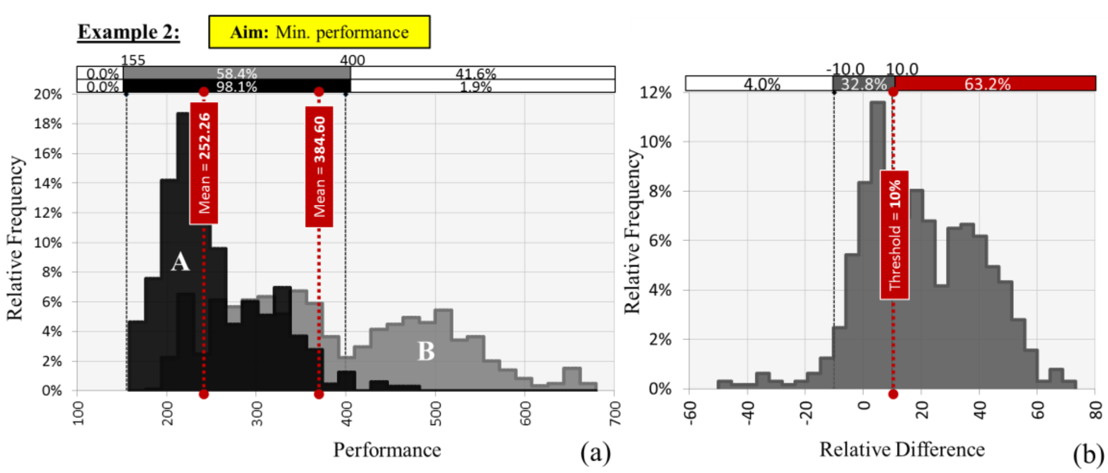



**Figure 3.7(a) Outcome comparison between alternative A and B, (b) Relative difference between alternative A and B (Example 2)**

Another example is shown (Example 3) to demonstrate the difference in outcome between relatively similar alternatives, as shown in Figure 3.8-a. In this case the measure is normalized energy consumption, so the smaller the better. The means of alternatives A and

B are 371.92kWh/m$^2$ and 384.6 kWh/m$^2$ respectively, which is relatively a marginal difference. Relative difference between the two alternatives is computed (Figure 3.8-b), which reveals that there is no value above 1.5%, hence there is zero confidence of one alternative being better than the other with (which we decide based on at least 10% difference). In this case study alternative A and B are relatively indifferent and a decision cannot be made between them with confidence. It basically means that the difference between A and B found from a deterministic assessment gives the false impression that the one with lower value is the preferred solution. The uncertainty analysis shows that such choice cannot be made with sufficient level of confidence.

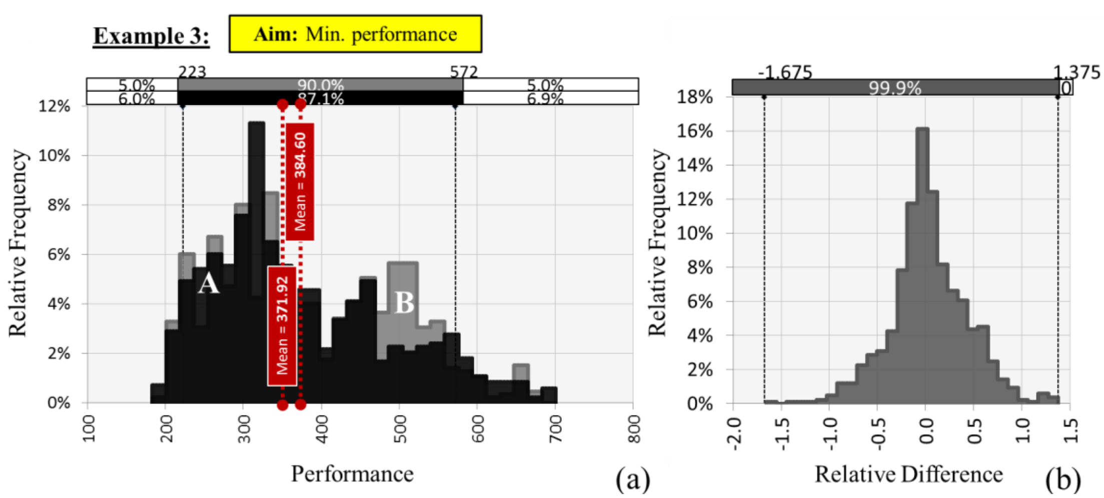



**Figure 3.8: (a) Outcome comparison between alternative A and B, (b) Relative difference between alternative A and B (case study 3)**

Assuming that two distributions are given for performance measure for two alternatives A and B, a decision-maker has complete confidence in a decision if the two distributions do not overlap, indicating that one alternative is always better than the other as far as the particular performance is concerned. This is seldom the case as the more common situation is overlapping distributions. In some case this calls for another criterion that may actually be the leading one to make the correct decision. In this approach it is relevant to look at the expected mean of either distribution but also at the probability of occurrences at the long tail of either distribution (which may be inconclusive), but also at the probability of occurrences at the long tail of either distribution, especially in the undesirable range of performance outcomes. In such case one will favor the alternative that has the least occurrence in that region, i.e. the alternative that minimizes the risk of occurrence in this undesirable range. Sometimes the mean criterion and risk avoidance criterion suggest different choices, hence one alternative may not be preferred over another with confidence. In general, the preferred alternative can be selected based on the first (mean) criterion, but there is a possibility that in particular design development, this alternative, is no longer preferred if the downside risk is bigger than acceptable.

The aforementioned undesirability test between alternatives is based on comparing the probability that an outcome stays within preferred limits. Assuming a case in which the aim is to maximize performance (Figure 3.9), the minimum preferred limit is 40. Based on this criterion alternative B has 12.5% chance of falling below preferred limit while alternative A has zero probability to be in that range (Figure 3.9). However, this method cannot always be applied in practice, as the decision maker doesn't always have a cut off limit of a performance indicator clearly defined, especially for indicators that cannot be directly linked to cost.

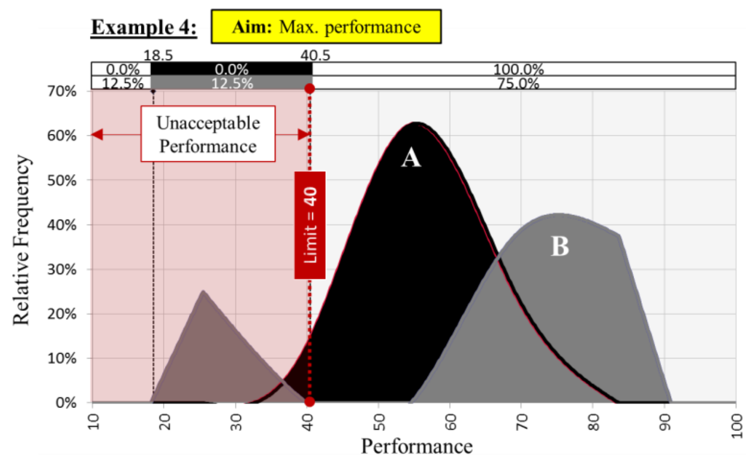



**Figure 3.9: Comparison between alternative A and B based on determined limit**

In order to make a decision among different options under uncertainty, a decision maker needs to be confident in the outcome of the decision. A decision is made with full confidence if the probability distribution of one option shows a better mean value and less risk. In the absence such a dominating option, there may be different levels of downside risks associated with each alternative. This means that, the degree of confidence in the selection of an alternative is subjective to the decision maker's acceptance of this downside risk.

## 3.4 Conclusion

In current approaches in urban design, a systematic method for alternative generation, analysis and selection in early design rarely exists and the design process is heavily dependent on the designer's experience and creativity. In the divergent phase there is no rigorous framework to generate more promising alternatives, whereas in the convergent phase, there is a lack of tools to make and validate decisions and provide confidence in alternative selection. In particular the current absence of design uncertainty consideration in the analysis and selection makes it necessary to investigate a better approach to performance-based urban design at the early stages. The aim of this approach is not to find the absolute best solution as it can typically not be identified at this stage anyway, but to guide designers through a design space that they construct and explore, offering them an approach to make rational choices

In this research, a new methodology is proposed for performance evaluation by taking into account the uncertainty posed by undecided parameters. This will be illustrated for two concrete criteria that govern urban design in the early stage. The main argument for this is that it helps the designer to identify those design alternatives that have more probability in achieving preferred performance levels. In this respect, the proposed approach does not aim in identifying purely optimal solutions; it aims instead to support design exploration, in which the designer has the freedom to intervene to address the search process and to extract knowledge from generated solutions (Turrin, et al., 2011).The proposed method, takes the iterative nature of design into consideration by allowing the designer to iteratively make design decisions. As new parameters get decided at different decision points, information and outcomes are updated impacting the estimation of the remaining undecided parameters, representing how a new decision of one parameter will affect other interrelated parameters.

# CHAPTER 4. RESEARCH METHODOLOGY

## 4.1 Overview of the Proposed Approach

Currently, in a performance-based design approach, performance criteria and preferences are determined by the designer or rather decision maker to evaluate alternatives to see what the best choice is to satisfy the preference. This mandates design parameters to be known, making it a useful approach for existing and complete designs. However, it’s questionable to apply such approach in early design, when many design parameters have not been decided upon.

In this chapter, the methodology for applying performance-based design in early design as outlined in the previous chapter is implemented in the context of urban design decisions. Design parameter uncertainty is incorporated and based on combination of these design parameters, multiple urban fabric alternatives are generated, and design option space created. Design options are then assessed, and an outcome impact space produced (as explained in detail in section 2.2).

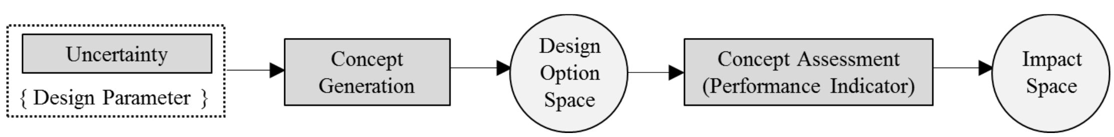



**Figure 4.1: General overview of proposed approach**

Each step of this approach will be discussed in detail (Figure 4.1). Urban design parameters and their hierarchy is explored in concept generation section and performance indicators are proposed as criteria for concept assessment. Uncertainty in undecided design parameters has impact on the evolving design option space which calls for to an application of decision making under uncertainty during the design process.

## 4.2 Formulation of the Concept Generation Process

An urban layout is a hierarchical geometric configuration consisting of a street networks and city regions, such as: quarters, blocks and lots. The street network is a planar graph with nodes and linear edges. The nodes have the following attributes: a two-dimensional location and hierarchy attribute (major, minor). The edges or street are line segments with hierarchy attribute (major, minor). The induced cycles of the street graph give rise to blocks (represented by polygonal faces). The blocks can be further subdivided into building lots. The latter store land use type, which then determines setbacks required to determine buildable area on the lot, leading to outlining the building footprint (Weber, et al., 2009).

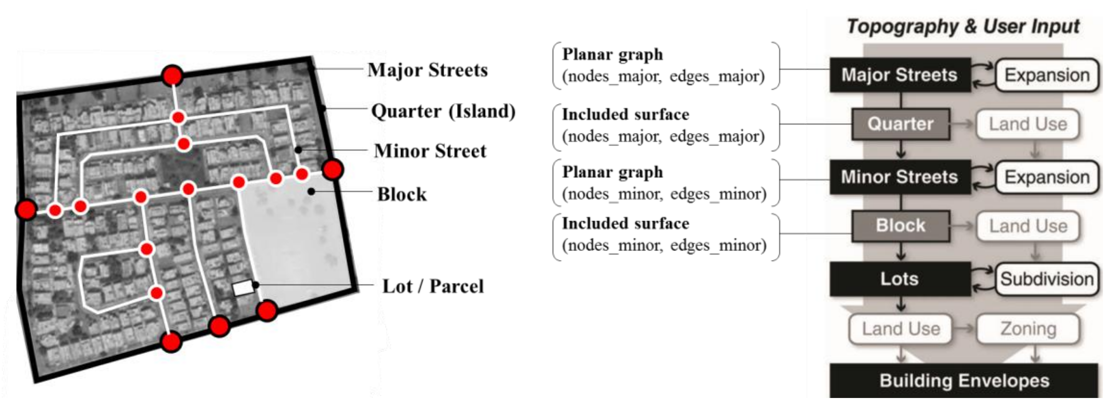



**Figure 4.2: Components of an urban fabric, based on (Weber, et al., 2009)**

Based on the literature, urban design can be treated as an additive process that consists of several steps, which are: creation of road networks, extraction of urban blocks, defining land use, parceling, buildable area boundary definition and building footprint placement. A process for urban fabric generation is formulated as per this additive process and different design parameters are associated with each phase.

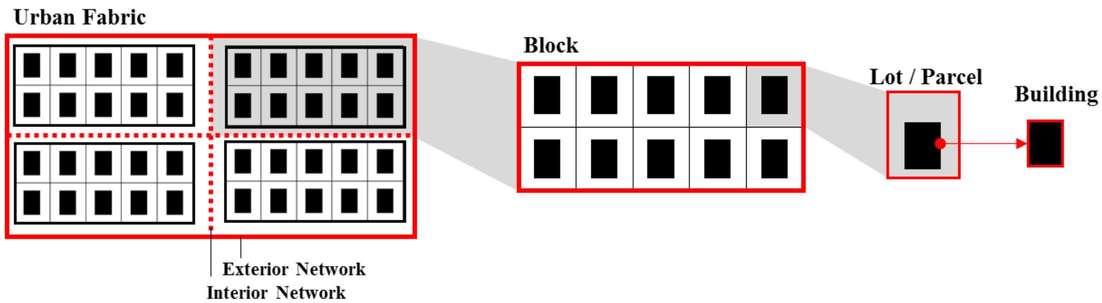



**Figure 4.3: Hierarchy of urban elements**

Based on the logic presented by Bielik, Schneider and Koeing (Bielik, et al., 2012) in the form of their Grasshoper3D analysis toolset “Decoding Spaces”, an urban fabric generation logic is established. In this approach, urban components are codependent and generated in a step-wise format, where one decision leads to another and in which the impact of changing one parameter is reflected on remaining codependent parameters (Figure 4.4). The scope of this research focuses on urban fabric, which consists of a collection of blocks, as well as network that surrounds these blocks. The boundaries of the fabric are drawn in the middle of access roads and the size of fabric is determined by the level of spread of different islands within the fabric. Urban block comprises lots and non-built space, which is used as playing field, public spaces or parking area. The border of an island is defined by the surrounding public streets or by lot boundaries. Lot, also known as parcel or plot, is the sum of built and non-built (predominately private) areas designated for building and the border of the lots is defined by legal boundaries specified in the cadaster. The area of the building is the same as the built area of footprint, the borders of the built area are defined by the edges of the building footprint (Pont & Haupt, 2009).

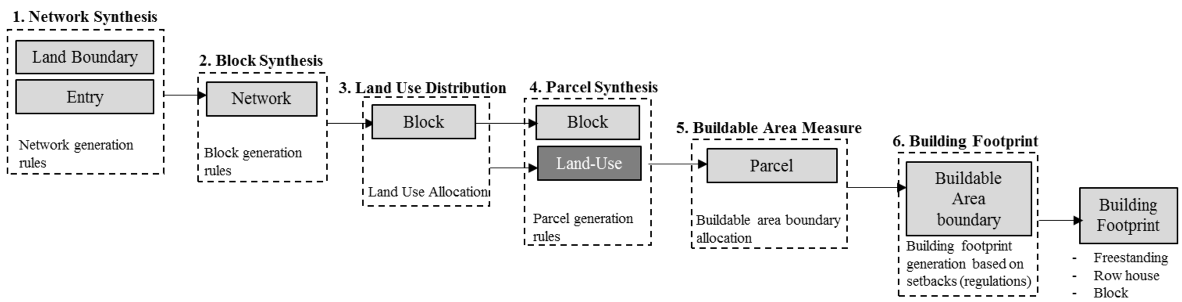



**Figure 4.4: Urban Fabric concept generation process**

Understanding the urban fabric generation process is crucial for identifying moments of decision making and design parameters associated with generation steps. Urban design, as mentioned earlier is a complex and creative process and translating the entire process into an (automated) computing problem would limit designer's creativity. However, there are parts of the process that are routine and in some sense redundant and it would significantly reduce design exploration time if they were automated. Hence the proposed divergent process (Figure 4.5) is subdivided into: user defined steps, in which the designer is in full control of the generation process, and automated steps, where the designer controls the design parameters, but the generation process is automated.

The steps that are user defined are: Land boundary definition and road network allocation and land use classification. Although there are tools and plugins that can automate road network synthesis (Miao, et al., 2017), in the proposed approach this step is viewed as an expert-driven creative process. The steps that are automated in the urban generation process are: (1) Block generation, where street offset is a design parameter that defines the block outline by offsetting it from the street network. (2) Parcel generation, by defining required parcel length, parcel width and street offset, blocks are subdivided into parcels. (3) Buildable area, defined by the boundary where a building can be placed is determined by defining road, side and back setbacks. (4) Building Footprint is the built-up area footprint on the parcel and can be defined by setting building type and its geometric properties (building length, width and height).

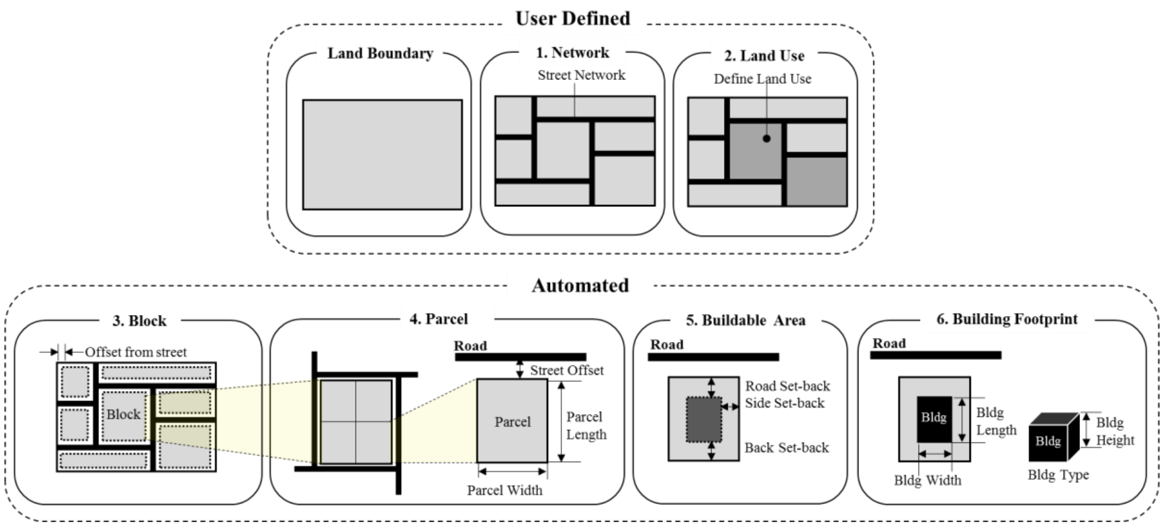



**Figure 4.5: Design parameters associated with the urban fabric generation process**

The aim of establishing a concept generation process is to evaluate the urban performance in the assessment phase and study the impact of design parameter uncertainty in this assessment. This study does not claim that the proposed urban generation method is the most optimal one as it is not the focus of this research, it is rather regarded as a typical generation phase that has the role to populate the option spaces for consecutive decisions.

### *4.2.1 Design Option Space: Parameter Range and Constrains*

Due to multiple undecided design parameters during early design, a calculated performance outcome is inherently uncertain, making a deterministic analysis of performance questionable for the following reason. The complex and ill-defined nature of urban design, particularly in early design makes it extra difficult to predict performance measure as a deterministic value, as this deterministic outcome will most probably not remain valid after design proceeds in an unpredictable direction. Because the final form of the design and how it will evolve are unknown at the earlier stages, the role of undecided design parameter uncertainty should play a role in early design decisions.

Although many studies focused on comparing techniques for sensitivity analysis and propagation of uncertainty, these techniques have not pervaded mainstream simulation tools. There has been no concern given to the question: "how quantitative uncertainty of predicted performance can be used to better-inform a design decision?"

Defining the uncertainty for each design parameter is hard and as there is no available theory, it should obviously be based on extensive design experience. It will drive the assignment of plausible ranges and choice of particular probability distributions. This information can be extracted from literature, experiments, rules of thumb or experience, as there is no general rule on how to quantify this uncertainty.

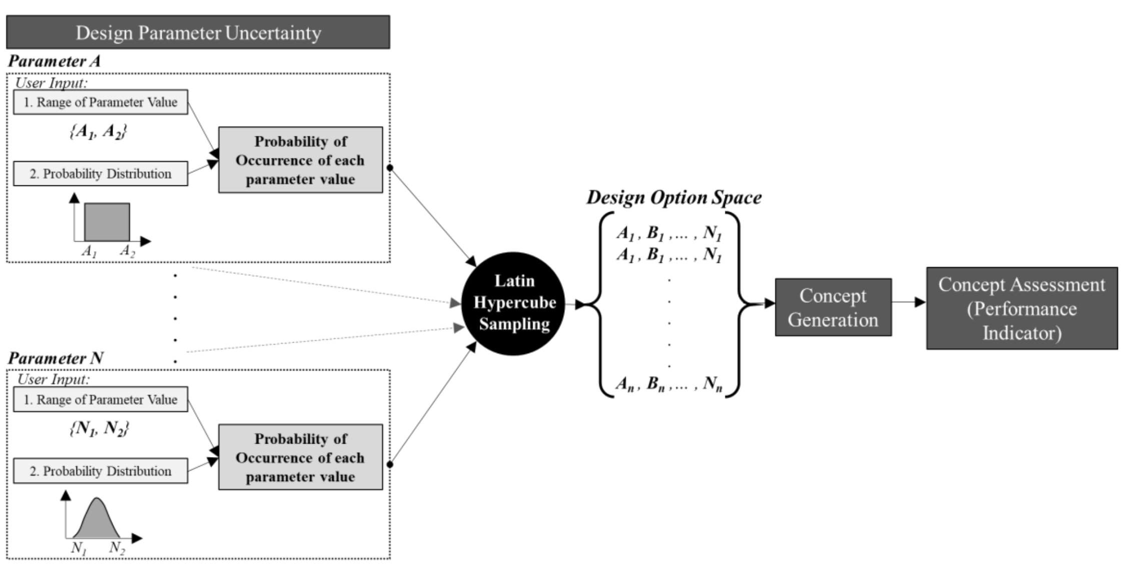



**Figure 4.6: Application of parameter uncertainty in proposed approach**

The most widely used method for propagating parameter probability distributions through an assessment model is Monte Carlo simulation. However, it has one drawback, it requires a large number of model evaluations if regular sampling is used. One way to avoid this is the use of clever sampling, e.g. Latin Hypercube Sampling, which uses a stratified sampling method (Figure 4.6). The domain of each parameter is subdivided into N disjoint intervals (strata) with equal probability mass. In each interval, a single sample is randomly drawn from the associated probability distribution. Application of this technique provides a good coverage of the parameter space with relatively few samples compared to simple random sampling (crude Monte Carlo) (Malkawi & Augenbroe , 2003).

Unlike engineered products, urban fabric parameter ranges and probability distributions cannot be specifically determined, as each area and sector and country have their own guidelines and rules. Hence definition of parameter ranges and their probability is based on decision maker’s preference, designer’s experience while adhering to limitations established by local guidelines.

### 4.3 Formulation of Concept Assessment

There are multiple tools and platforms available to validate performance of existing urban settings, these tools are of high resolution and require detailed information and are mostly used at later stages of design, such as when choosing between or verifying compliance of fully developed options or for existing urban forms to evaluate their retrofit potential. Complex outcomes that need spatial and temporal simulations and aggregation, such as urban energy consumption and outdoor thermal comfort are typically computed through high-resolution tools. However, in early design low resolution models are preferred as at this stage, the design typically goes through many iterations testing conceptual (coarse) alternatives.

### *4.3.1 Outcome Impact Space: Confidence Assessment and Prediction Interval*

Normative decision theory literature suggests that for preference elicitation, one needs to resort to axiomatic utility theory. This is not pursued here as it is outside the scope of this thesis. It is assumed that for every single criterion the decision maker has a clear understanding of his preferences for the different criteria that are chosen to assess the alternatives. When it comes to the trade-off between criteria, this is typically not the case and it will be hard for designers to determine the trade-off in a rational way. In this thesis, it is assumed that designers have experience in comparing different options under multiple criteria. This thesis focuses on how to inform the decisions and especially show when the uncertainty in outcomes leads to more emphasis on one criterion and less on another.

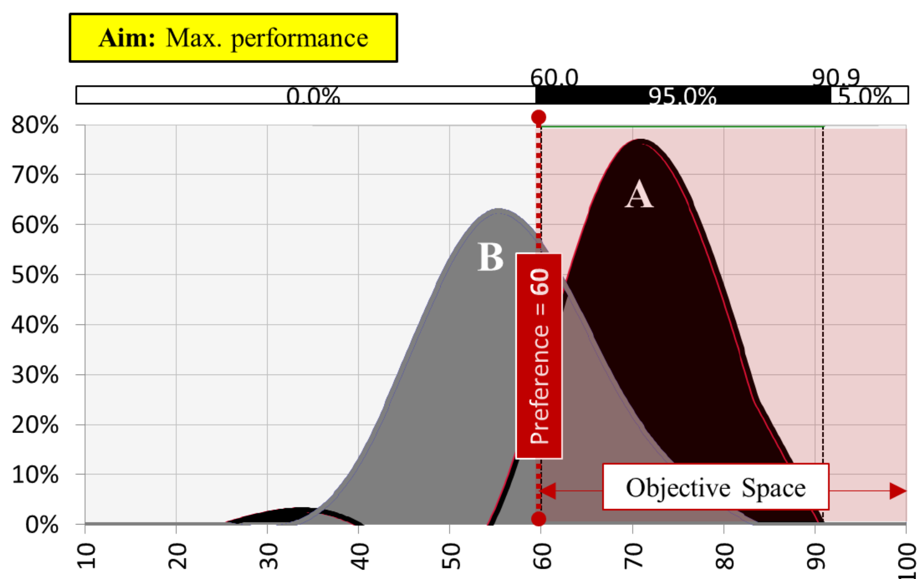



**Figure 4.7: Objective space within outcome impact space**

### 4.4 Urban Performance Measures

Modern cities have received heavy criticism, especially in the early Sixties in the name of the ‘magic’ of the old cities (Jacobs, 1961). This claim was not limited to aesthetics, it included livability as the modern cities are becoming hard to live in. The social success of old urban settlements, which was conceived by the unpredictable outcome of safety, trust, economic vitality and diversity sprouts from the complex, unplanned interactions of countless different routes and experiences in a suitable environment. Hence, we need to understand and analyze these complex systems to be able to design in a better manner.

The fields of architecture and urban design have so far resisted scientific formulation, which is in part because of the underlying complexity. Efforts in the past have been mainly focused on identifying the process that produces forms, but this has had little impact on actual development. In order to determine whether a particular design satisfies a performance requirement, a certain measure is used to quantify the required or expected performance as well as the achieved performance. Our focus is primarily on the latter as this is where simulation plays a cardinal role. There are four notable attempts in quantifying urban performance:

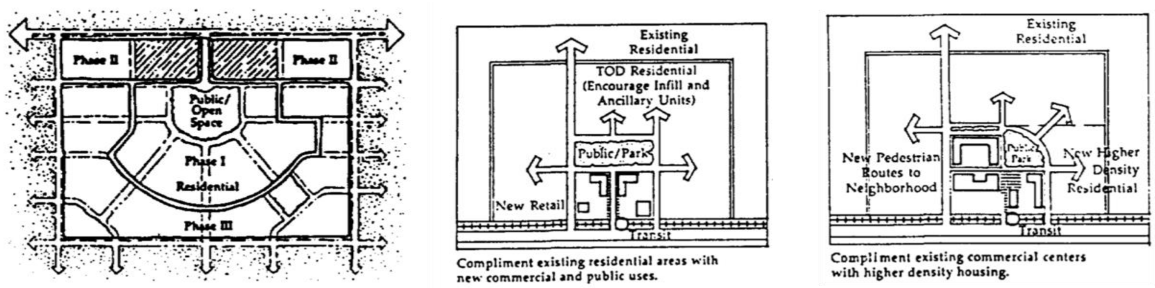
1. Christopher Alexander (Alexander, 1964, 1965, 1998, 1977, 1987), treating the urban components as patterns.
2. Batty & Longley (1994, 1996), casting of urban patterns as fractals emphasizes their linked hierarchies and microstructure.

3. Hillier's (1996, 1984) formulation of urban questions in terms of relationships and movement sheds light on the forces governing the growth of a city.
4. Kevin Lynch (1981), focused on giving visual form to the city.

As deeper theoretical understanding of cities is what we need, we are also at a stage where fundamental questions about our sustainable future cities are raised. It is widely acknowledged that to make cities sustainable, we must base decisions about them on a more secure understanding than what we have now. But what is better understanding? Cities, physically, are stocks of buildings linked by space and infrastructure. Functionally, they support economic, social, cultural and environmental processes. Cities are means-ends systems, where means relate to the physical aspect and ends relate to the functional aspect. The most critical area of ignorance is this relation of the physical city to the functional city and the fact that sustainability is about ends and is controlled mostly by means has exposed our ignorance in this critical area (Hillier & Hanson, 1993).

This thesis focuses on two physical aspects of the urban fabric, the first is the built part and second is the unbuilt part (outdoor open space). The measures that are considered for evaluating the performance of built space are indoor daylight and operational energy consumption, whereas the measures that are used for outdoor space are connectivity, visual quality and outdoor thermal comfort, as they are among the major contributors of outdoor space usage, hence "livability" of the open space. Some of these measures are well established as computable values (outdoor thermal comfort, daylight, energy consumption), whereas for others, numeric values cannot be readily computed such as for connectivity and visual quality. In the latter cases, values are extracted from literature, translating a suitable functionality assessment method to numerical values.

In this section, literature treating each performance measure will be reviewed, and a computing methodology will be extracted from previous studies and the proposed methodology will be applied on case studies. Three case studies are borrowed from transit-oriented development guidelines for city of San Diego (Assocaites, 1992). They will be used to test suggested performance indicators (Figure 4.8).




(a) (b) (c)

**Figure 4.8: Urban fabric based on transit oriented development guidelines: (a) Guideline 1A, (b) Guideline 2D, (c) Guideline 1A (Assocaites, 1992)**

Based on the assumptions of previous chapter, a workflow for urban fabric generation has been established, in which site boundary, network geometry and land use allocation is determined by the user and the uncertainty in the parameters is introduced at the building level, starting from parcel definition and ending in building footprint allocation. This procedure was followed to limit the number of generated options to a manageable figure, and not take away designer's creative freedom. Introducing the uncertainty in the building generation part of the workflow also helps in limiting the number of generated options and getting meaningful distribution results rather than distribution that have wide ranges, making it almost impossible to make an informed decision.

### *4.4.1 Performance Measure-1: Network Connectivity*

#### 4.4.1.1 PM-1: Background

A central component of the human intellect is the ability to establish connections. An urban setting can be decomposed into human activity nodes and their interconnections. The connections are then treated as a mathematical problem. Empirical observations verify that the stronger the connections, and the more substructure the web has, the more life a city has (Alexander, et al., 1977; Gehl, 1987). Hence, urban design is considered most successful when it establishes a certain number of connections between activity nodes (Salingaros, 1998).

The process that generates the urban web can be summarized in terms of three principles:

a) *Nodes*: the urban web is anchored at nodes of human activity; whose interactions make up the web. These nodes can represent either architectural elements or intersection points of edges.

b) *Edges*: connections between nodes, can be connection between complementary nodes (not like nodes) or between adjacent nodes in case of street network. There can be multiple connections between nodes, successful paths are defined by the edge between contrasting planar regions, and form along boundaries.

c) *Hierarchy*: hierarchy of connections is not always present in urban web, but it allows to categorize the connections as per usage and properties.

When representing a transport network as a graph, the links in the network become edges in the graph and nodes become vertices in the graph. It is then possible to use graph-theoretical indicators to analyze network structure and capture properties such as 'connectivity'.

Graph theoretic analysis uses vertices to represent primary elements, such as: landmarks, people, rooms, buildings and intersection. Whereas, edges represent relationships between those elements, such as: movement, exchange and route.

Graph theory can be applied to different scales (as shown in Figure 4.9), ranging from city level to represent transport routes, to block level showing the interaction of street network, to street level representing pedestrian pathways and space use. In this research our focus will mostly be on the urban block, where edge represents street or pathway segment and node represents junctions where one or more edges intersect.

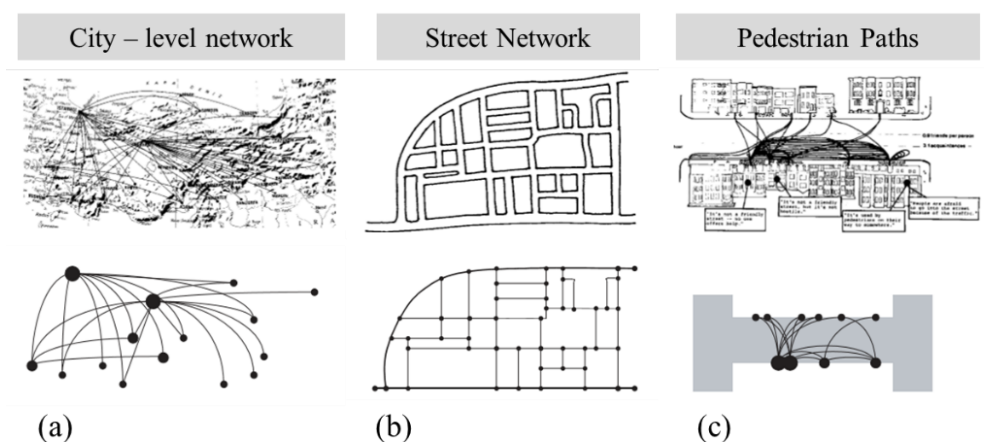



**Figure 4.9: Application of graph theory in different scales. (a)Pattern of airline network: a 'hierarchy of nodes', (b) Street network: a 'hierarchy of routes', (c) Network of pedestrian paths: a 'hierarchy of nodes' (Marshall, 2005).**

One of the critical aspects of an urban design is to understand how people move in the fabric and experience different spaces. Since these experiences are subjective and are traditionally difficult to be represented in computer simulation. However, we can come close to measuring specific aspects of this experience if we treat the problem more narrowly. Examples of such specific applications include how far people travel between different programs in space (adjacency), potential bottlenecks, where such movement is concentrated (congestion). Occupant-level metrics give a deeper understanding of urban spaces from point of view of occupants, and often are more related to the client needs as compared to the overall fabric form. For this type of urban network computation, ‘graph theory’ is used, which is based on data structure called ‘graph’.

A ‘graph’ can be defined by list of nodes (vertices) and list of edges, which connect sets of two nodes and represent relationship between them. Graph structure is flexible and can represent many types of relationships. In spatial applications, nodes typically represent locations in space, whereas edges represent connection between spatial locations. These connections can represent walkways, roads or public transit line. The arrangement and connectivity of nodes and links of a network is referred to as its typology.

The long-standing interest in measuring the spatial structure of urban fabric and its networks has been driven by the inherent impact of urban structure on the performance of transportation systems, as well as its subsequent effect on land use and urban form (Marshall, 2005). Quantifiable performance indicators can abstract the properties of a complicated network structure and could assist in exploring different network options in a spatial and temporal context.

In cities, the relation between form and function passes through space and how we organize space into configuration is key for city form and the way human function in cities. Hillier and Hanson (1993) set a central proposition that the fundamental correlate of the spatial configuration is ‘movement’. Movement largely dictates configuring of space in city and is mostly determined by spatial configuration. This theory based on the recent research findings that suggest that the structure of urban grid, which is purely spatial configuration, is the most powerful and single determinant of urban movement. Therefore, it is suggested that well-functioning cities are thought of as “movement economies”.

There are relationships between formal characteristics of space and how people use it. This suggests that space is given as set of potentials and individuals exploit these potentials in using the space, making the relation between space and function ‘analyzable’ and to some extent predictable.

An urban system – by definition- is one which has at least some origins and destinations more or less everywhere. Every trip in an urban system has 3 elements: origin, destination and by-product, which are series of spaces that are passed through on the way from origin to destination. The by-product is determined by structure of the grid, therefor urban grid has crucial effect in increasing or diminishing degree to which movement by-product is available as potential contact. Relation of grid structure and movement generate “urban buzz”,

#### 4.4.1.2 PM-1: Calculation Methodology

As discussed in the previous section, “good space” is used space and most urban space used is by movement. Informal space use is movement related and urban grid through its influence on the movement economy is the fundamental source of multi functionality that gives life to cities.

The methodology proposed for network analysis is integrated with the urban fabric generation process. It takes the network design, urban grid entry points and destination as an input and extracts the paths with their frequency of use based on Dijkstra's algorithm, which is an algorithm for finding shortest paths between nodes in a graph, producing shortest path tree. The overall approach can be summarized in three main steps (Figure 4.10):

a) Define urban grid and land used, based on which entry points destination areas are determined.
b) Network is subdivided into links and nodes and all possible routes are identified based on Dijkstra's algorithm.
c) By-product areas are determined based on defined routes in (b).

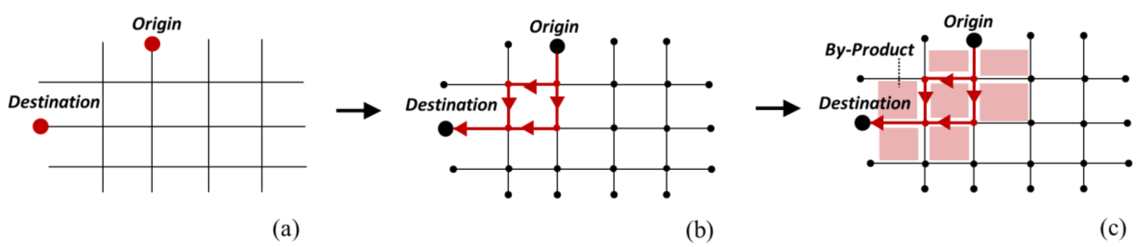



**Figure 4.10: Network connectivity methodology overview**

For generating the outcome for performance indicator 1, the following computation stages are proposed (Figure 4.11):

1. Urban network is deconstructed to basic graph structure: vertices and edges

2. Origins and destinations are identified from given vertices, based on land use allocation. Origins being the entry points to the urban network and destinations are commercial and public spaces.
3. Based on Dijkstra's algorithm, path tree is allocated on the urban grid, along with usage frequency of each edge.
4. Blocks are linked to generated path tree and by-product spaces are identified.

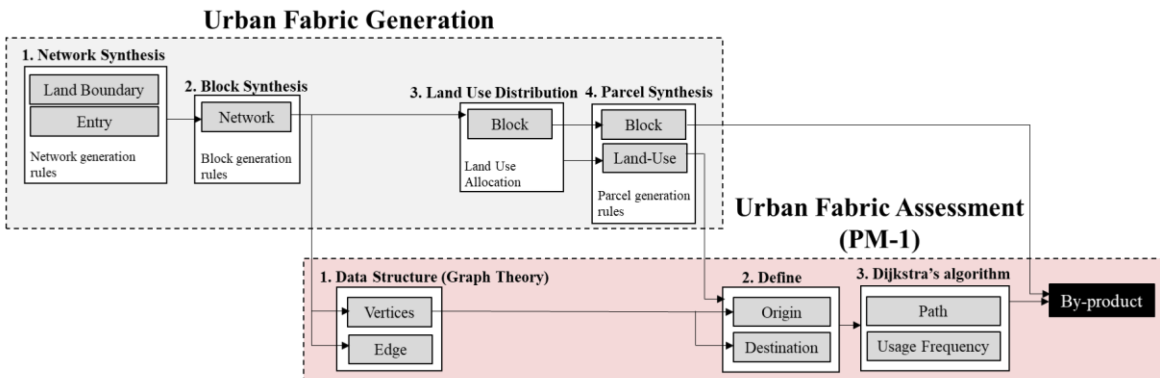



**Figure 4.11: Proposed framework for urban fabric assessment (PM-1) integrated with generation process**

The performance indicator used to represent connectivity of the urban network is percentage of by-product blocks in the urban setting. The higher percentage of by-product blocks indicate more movement and lower percentage imply limited movement. For an active urban fabric, the aim is to maximize the by-product percentage.

#### 4.4.1.3 PM-1: Application

Three case studies from transit-oriented development examples (Figure 4.8) are chosen to compute the percentage of by product. The aim of this comparison is to find the urban fabric with the most potential of by product spaces, hence most potential for urban movement.

If the three case studies are compared as presented in the guideline, with specific land use, origins and destinations, the result is traditionally a deterministic value (Figure 4.12). As the aim is to maximize the by-product value, case study 1 is a clear choice as it provides highest percentage of by-product as compared to other case studies.

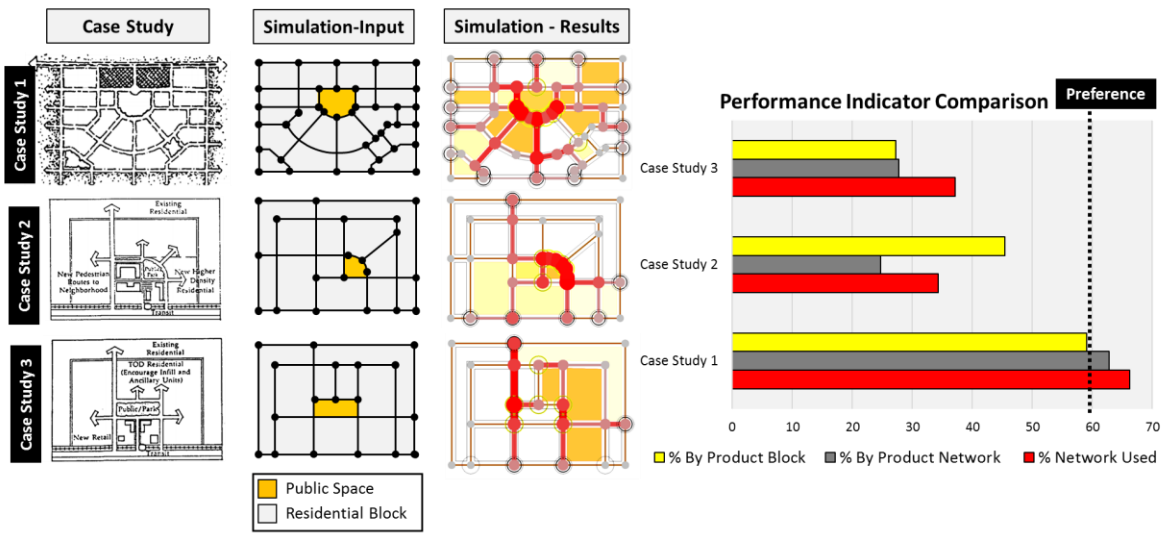



**Figure 4.12: Case study for performance indicator 1; deterministic result comparison**

With intention to explore the full potential of the case studies, uncertainty was introduced in the land use category. Instead of using specified locations for public space, the location is sampled across plausible values, and values of resulting performance are recorded for each sample, resulting in a probability distribution instead of deterministic outcome (Figure 4.13). Looking for the most desirable alternative after introducing uncertainty is no longer an obvious choice. Assuming that aim is to choose an active urban fabric, which has high percentage of by-product and 60% being minimum preference limit, the three case studies are compared. It is evident that both options 1 and 3 have potential of having by-product percentage of more than 60%, however option 3 has a risk of scoring less than 40%, based on public space allocation. Whereas option 2 only has a 25% chance of achieving by-product more than 60%, however it does not have the risk of scoring less than 40% like option 2. Based on this comparison case study 1 is the choice with the least risk and would be the favored alternative for a risk-averse decision maker.

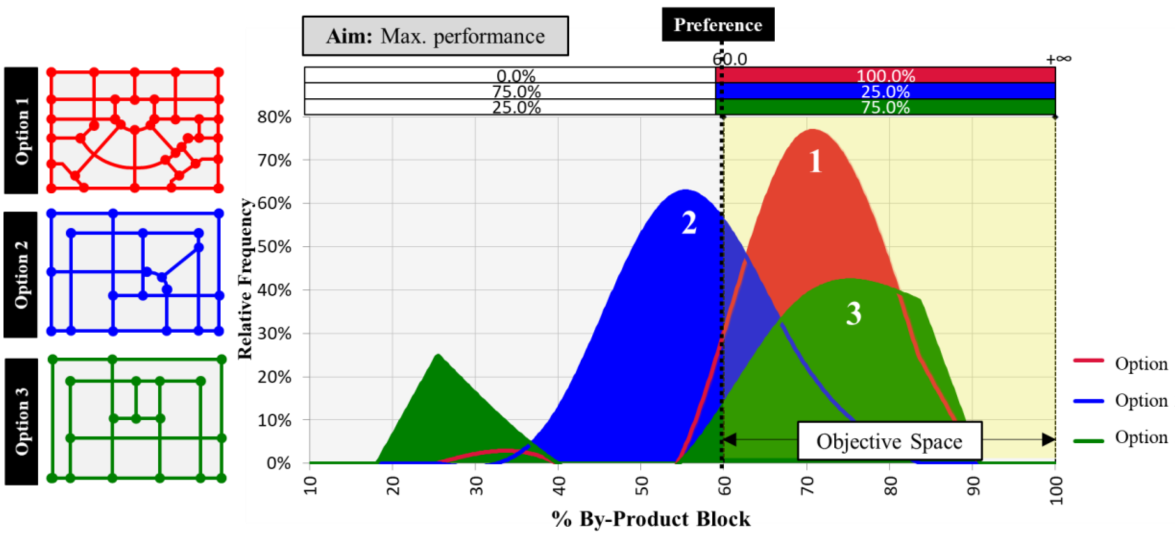



**Figure 4.13: PI-1 outcome comparison between three road network options**

### *4.4.2 Performance Measure-2: Visibility*

#### 4.4.2.1 <u>PM-2: Background</u>

Another aspect of outdoor space performance is the visual quality of the outdoor space. Such human-level measure of space has witnessed major development in last few decades. The first attempts to assess the environmental quality of urban spaces based on perception were introduced in the late fifties and in the sixties as result of interdisciplinary studies in architecture, psychology, anthropology and sociology. Edward T (1960, 1966) opened up a series of applications in architectural and urban design, which investigates the cultural aspects that involve human behavior in urban space (Hall, 1960; Hall, 1966).

If we aim for a low resolution (modeling) approach to perform the, a suitable of measures should be used that quantify human-level perception of a space but do so though fairly simple geometric (statistical) calculation. One of the most common techniques to achieve this is the “isovist” (Figure 4.14). Originally the notion of ‘isovist’ was presented by Tandy (1967) in the field of landscape geography, but Benedikt (1970) first introduced the concept in architectural studies. Isovist is defined as the field of view, from a specific standpoint. An isovist can also be understood as the area not in shadow cast from a point light source. In scientific literature, the isovist represents a horizontal slice through this field view taken at eye height and parallel to the ground plane, represented as 2-D polygon. Additional definitions have been added more recently, one of which was translated into Space Syntax theory, “an isovist is sum of the infinite number of lines-of-sight (or axial lines) that pass through a single point in space (usually at eye height) and occupy the same plane (usually parallel to the ground plane)” (Dalton & Bafna, 2003).

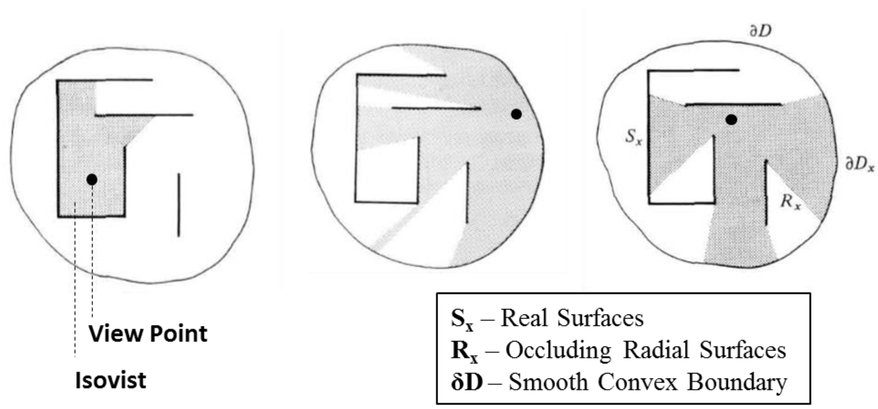



**Figure 4.14: Isovist elements (Benedikt, 1979)**

Using isovist as simple visualization geometry can be difficult to interpret as visualization alone does not provide numerical metrics which can be used as quantifiable objectives for a generative design workflow. To use isovist analysis, geometric representation is converted to numerical performance indicators that give quantitative measure of the space. Benedikt (1979) provided a set of measures that could be extracted from isovists to quantify spatial experience. Two of the measures that Benedikt focused on particularly were:

a) **Area of isovist:** describes the total amount of area visible from a point (Total Visibility in space).

b) **Perimeter length of the isovist boundary** describes the 'jaggedness' or complexity of the view, or how quickly the view changes as you leave the point (Total Complexity of space).

These measures quantify different aspects of how a person may experience the space and together give fuller description of space (Benedikt, 1979). A cramped space, such as a hallway will have low values for area and medium value for perimeter length, whereas an open space with obstacles will have a medium value for area and high value for perimeter length. An open, easy to navigate space would be one that has maximum visibility and minimum complexity.

Over the years most of the researches concerning isovist have gathered in the space syntax field of study, which works on developing tools and methodologies for statistically simulating spatial experience. However, for this thesis, the measures will be extracted from simple geometric calculations.

#### 4.4.2.2 PM-2: Calculation Methodology

Isovist calculates how much of the surroundings visible from any point in space. The isovist is computed by projecting a series of vectors from the point and seeing where the vectors intersect with geometry in space. These points can be connected to each other to form the total ‘volume’ of visible space. Although the isovist can be calculated as a volume in 3-dimensional space, it is typical in architectural application to compute only the 2-dimensional isovist in a given plan, as this makes the calculation much faster.

The following input are required for calculation:

a) **View-point:** Center of view cone, represented as point coordinate (x,y,z).
b) **View Distance:** Distance threshold from viewpoint in meters (View Radius)
c) **View Extents:** Field of view in degree.
d) **Obstacles:** Objects which potentially block views within specified distance limit, represented as list of mesh objects.

These inputs are used for computing field of view and the following output are measured:

a) **Cone Edges:** Geometry of view cone, each cone consisting an arc and two edges.
b) **View Distances (D):** Distance of each view cone matching the edge output.
c) **View Angles (Ɵ):** Angles of each view cone matching edge output.
d) **Unobstructed Percentage (U):** Percentage of total angle of views which are unobstructed within specified distance cutoff.

Summation of cone edge area gives the total amount of area visible from a point, “total visibility’, and summation of perimeter length of cone edges describes complexity of view, “total complexity” (Figure 4.15).

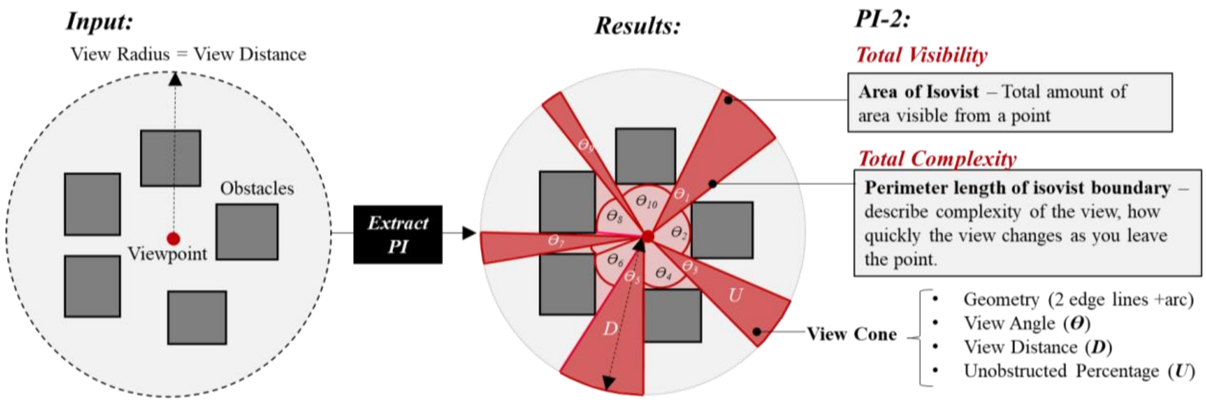



**Figure 4.15: Overview of performance measure-2 calculation methodology**

Position of the viewpoint and surrounding obstacles greatly influence visibility and complexity outcomes. In a case study generic urban forms based on Martin and March are used with analysis point at the midpoint of the fabric to compare total visibility and complexity based on urban forms. It is noted that urban fabric (c) provides relatively higher values of both visibility and complexity as compared to other urban forms, whereas urban fabric (f) has least outcome in both categories as the analysis point is highly confined in a dense urban fabric (Figure 4.16).

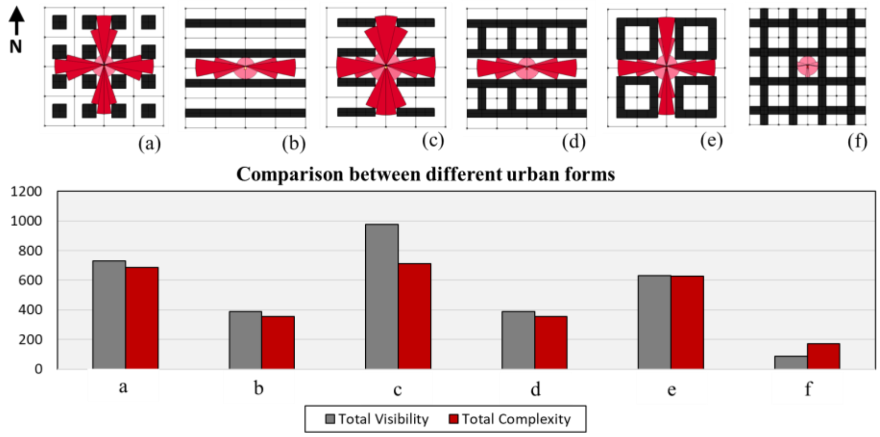



**Figure 4.16: Performance measure-2 comparison between different urban forms**

In another case study (Figure 4.17), an open space is subdivided into multiple points of analysis, visibility and complexity of different points are computed to demonstrate the impact of analysis point location. Mid-point (c) of the open space has highest value for visibility and complexity as compared to corner analysis points (a, b), as it provides maximum unobstructed view.

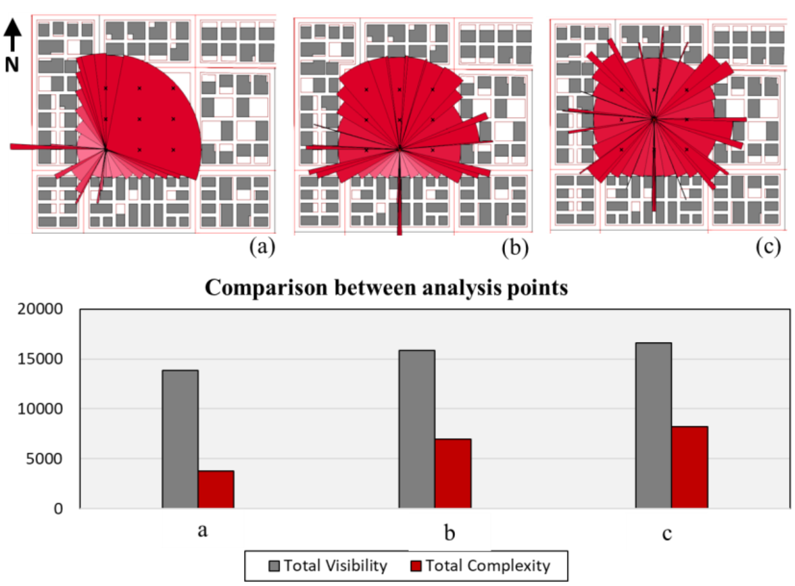



**Figure 4.17: Performance measure-2 comparison between different analysis points of an open space**

#### 4.4.2.3 PM-2: Application

Performance measure-2 uses two inputs from the urban fabric generation process, which are: "land use allocation", as open space is allocated at this stage and "building footprint", which represents obstacles blocking the field of view. Open space is subdivided into analysis points and the outcome is computed for each point in this analysis grid (Figure 4.18). The rest of the input parameters, view distance and extents are not related to urban fabric generation, they define the geometric extents of the view cone.

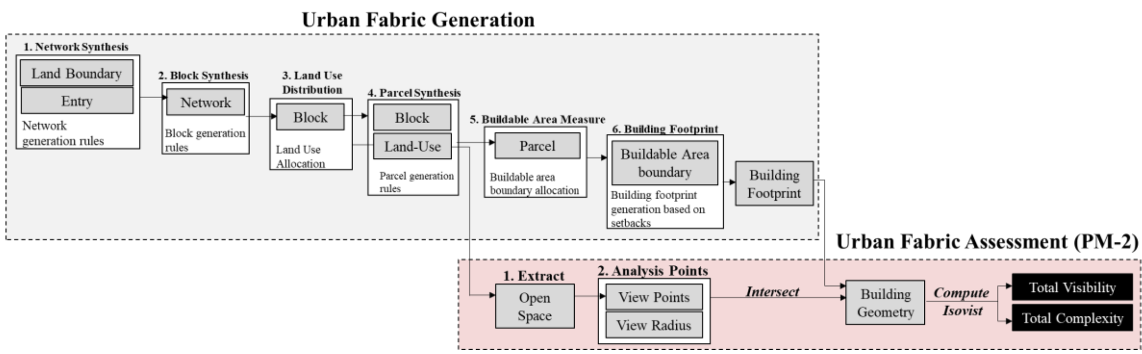



**Figure 4.18: Proposed framework for urban fabric assessment (PM-2) integrated with generation process**

Performance indicator -2 is applied at two different decision points. The aim of the first case study is to choose between three different urban fabrics based on the visual potential of open public space. Uncertainty was projected on plot size and building setbacks and simulation conducted for design space created with incorporation of both sources' uncertainty (Figure 4.19).

Two performance indicator distributions were compared for the three urban fabrics, i.e. total visibility and complexity. The aim is to maximize both visibility and complexity indicators to create an open space that is visually open and provides a sense of interest because of the visual complexity of space.

Based on the comparison of performance indicator distributions in Figure 4.19, it is evident that option 3 has the highest potential for achieving high visibility value, regardless of design parameter decisions in the design process. Whereas option 1 is highly dependent on design parameter decisions, because of which, this option cannot be selected with any confidence about the outcome.

Visual complexity performance distributions are also compared of the three case studies, based on this comparison, it is evident that only option 2 has the potential of achieving high visual complexity for few of the design parameter options in the generated design space.

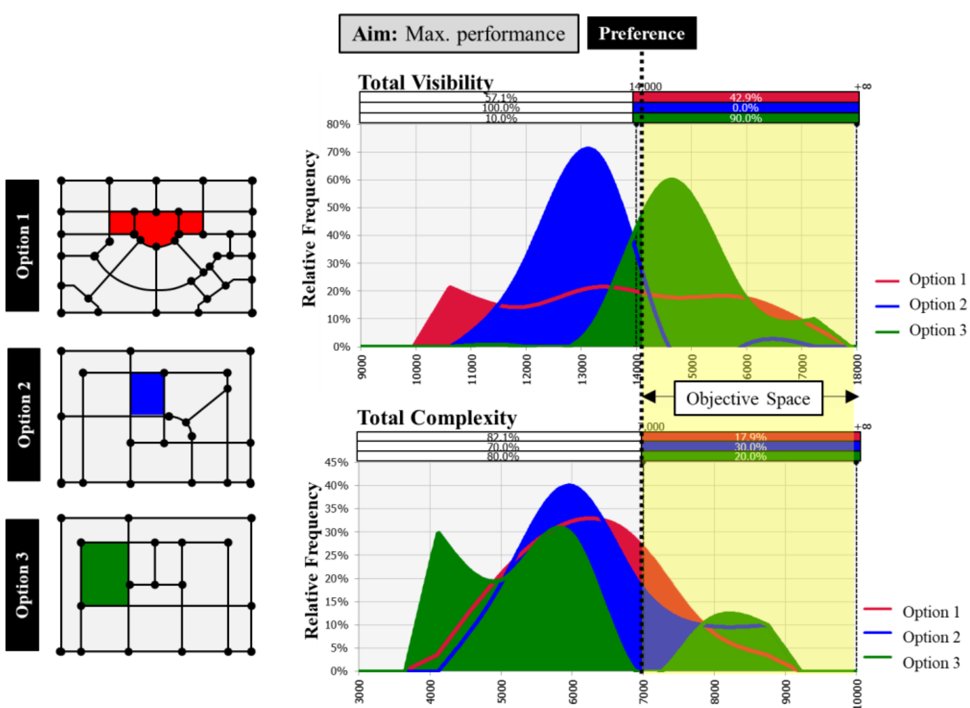



**Figure 4.19: Performance measure -2 comparison between different urban fabric options**

In the second case study same urban fabric is used, with the aim of finding a public space location with highest potential of total visibility and complexity (Figure 4.20). As compared to rest of the options, option 2 has the potential for high visibility value in the open space for most design parameter options. Whereas, for visual complexity performance, option 1 has the higher potential as compared to other options in achieving higher values.

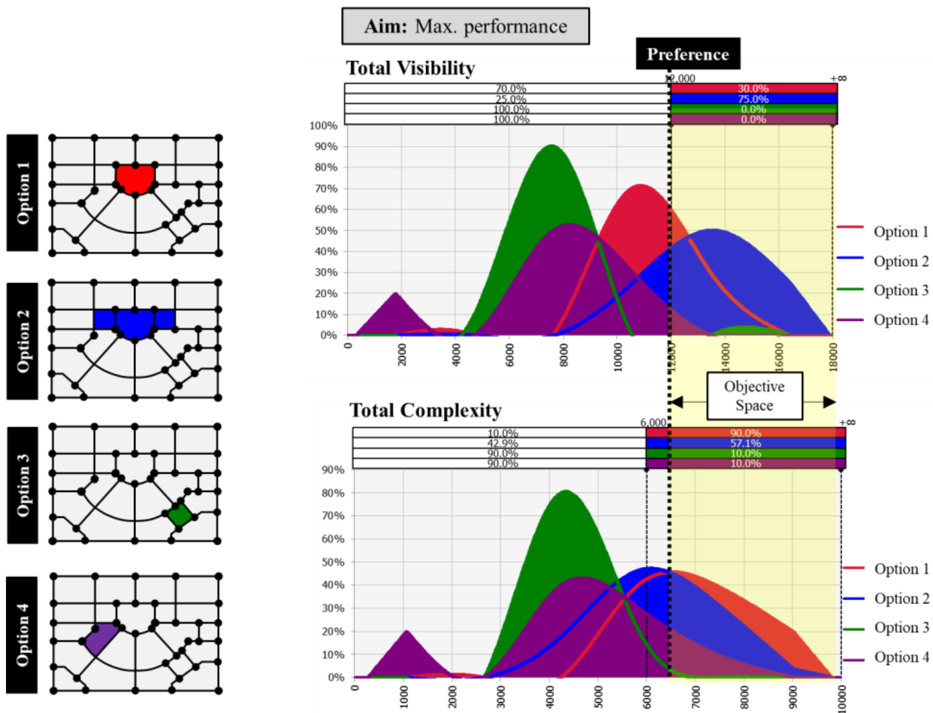



**Figure 4.20: Performance measure -2 comparison different open space locations in an urban fabric**

It is important to note that a clear choice between options is not always guaranteed in the proposed method, as it is not a single value deterministic comparison and design parameter uncertainty is propagated in the compared options, hence there is high risk level associated with uncertain parameters.

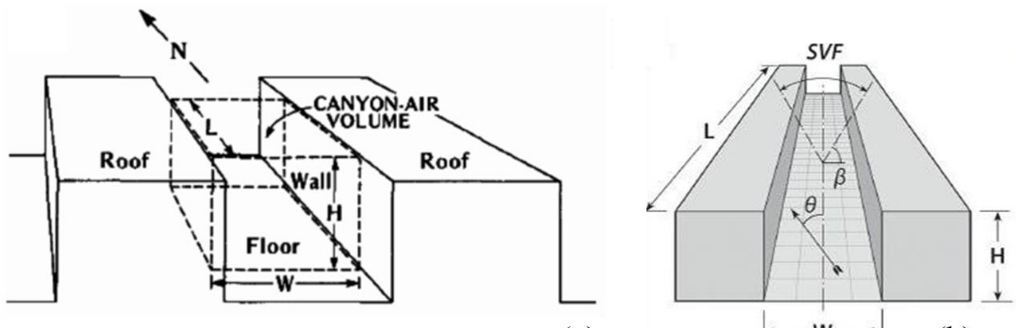
### *4.4.3 Performance Measure-3: Outdoor Thermal Comfort*

#### 4.4.3.1 PM-3: Background

Urban climatology studies the climate conditions within the urban area and the lower atmosphere. The field evolved from empirical observations to a practical branch of meteorology as more studies revealed the mechanisms behind the creation of the urban climate (Oke, 1987; Oke, 1982). Urban climatology studies the outdoor microclimate in an urban environment, which provides the urban context influence on buildings. Therefore some studies proposed climatology studies to be one of the central starting points of urban design (Landsberrg, 1981; Lowry, 1967). However, because of the "wicked" nature of urban design problems, climate-sensitive design problems need to be dealt with on a case by case basis.

Many researches correlated urban context geometry to the microclimate in existing urban settings in order to provide design guidance for new designs. One of the most common urban geometry characterizations used for these correlations has been the "urban canyon", which refers to a basic urban surface unit that is formed by walls, roofs and ground between two adjacent buildings (Nunez & Oke, 1977). It is commonly used as representation of outdoor space in an urban form. Geometry of urban canyon can be described using three measures: Aspect ratio H/W (Height/Width), SVF (Sky View Factor) and orientation. Aspect ratio is the ratio between the average height of adjacent vertical elements and average width of space. SVF is the sky dome that is seen by a surface and the canyon orientation is measured by the direction of the linear canyon space, as the angle between it and a line running north, measured in clockwise direction (Erell, et al., 2015).

These geometric representations of an urban space have been correlated to urban heat island (UHI), wind attenuation and velocity ratio (Oke, 1987) and albedo (relativity of reflected solar radiation) (Erell, et al., 2012).



(a) (b)

**Figure 4.21: (a) Schematic representation of urban canyon (Nunez & Oke, 1977), (b) Sky View Factor (Erell, et al., 2015)**

More details were added to urban canyon geometry to represent more complex cases, but the results are greatly dependent on the assumption of these variations, hence case specific and difficult to generalize (Erell, et al., 2012). On the other hand some studies relied on detailed models to represent real urban environment and used high resolution simulation tools for case specific analysis (Emmanuel & Fernando, 2007; Katzschne & Thorsson, 2009). Because of the complexity and uniqueness of urban settings, these findings cannot be generalized.

In order to use outdoor thermal comfort as a measure in early design, a simple computation model is desirable, but this raises the question: to what extent can simple urban geometrical variables predict the radiant environment? Urban radiant environment close to the ground highly affects the thermal conditions experienced by pedestrians and users of open spaces. The sum of all radiation fluxes to which a human body is exposed governs thermal comfort to a large degree. The sum of the radiant fluxes is directly correlated with the mean radiant temperature (MRT). Irradiation in the outdoor space is highly dependent on the openness of the sky vault, which is determined by urban geometry and its orientation. Both sky view factor (SVF) and ground view factor (GVF) are measures for the openness of sky and sun exposure (Chatzipoulka, et al., 2015). For a particular urban setting, SVF is assumed a constant for the space that ranges from 0 to 1, whereas GVF is a measure of the exposure to the sun and varies with time depending on the sun's position. For a given point the GVF value is either 0 (in shade) or 1 (exposed) (Figure 4.22).

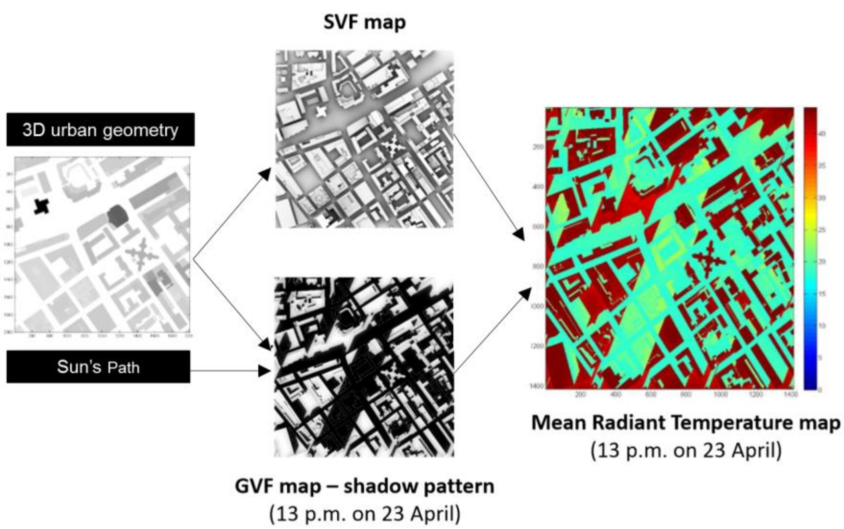



**Figure 4.22: Urban geometry related to radiant environment indicators (Chatzipoulka, et al., 2015)**

Predicting thermal comfort requires knowledge of multiple environmental and personal factors. Comfort indices are commonly calculated using four primary environmental factors: Dry bulb temperature ($T_{db}$), relative humidity (RH), air speed (v), and mean radiant temperature (MRT). Models also typically include personal inputs such as the clothing type and activity level. Other factors which are more difficult to model can have an impact on the thermal comfort, including a person's posture, and their bodily orientation with respect to the sun. Because the intention of this performance measure is to describe conditions for the general population, these personal inputs can be fixed at appropriate mean levels. For example, occupants are assumed to be at an activity level equivalent to standing, instead of more extreme high or low activity level (running or sitting) (Rose, et al., 2010).

#### 4.4.3.2 PM-3: Calculation Methodology

The proposed outdoor thermal comfort calculation method has been intentionally simplified so it can be used quickly for comfort prediction of outdoor urban space in multiple rapid design iterations. Effective radiant field (ERF), is used as a measure of the net radiant energy flux to or from the human body. ERF is used to describe the additional (positive or negative) long-wave radiation at the body surface when surrounding surface temperatures are different from the air temperature. The surrounding surface temperature of a space is commonly expressed as mean radiant temperature (MRT). ERF can be correlated to MRT as per the following equation:

$$ERF = \boldsymbol{f}_{eff}\, h_r\, (MRT - T_a) \qquad (2)$$

Where $\boldsymbol{f}_{eff}$ is the fraction of the body surface exposed to radiation, which is equivalent to 0.725 for a standing person (Fagner, 1970); $h_r$ is the radiation heat transfer coefficient ($W/m^2K$), and can be computed as a function of wind velocity: $h_r = 15.4\ \nu^{0.63}$ (de Dear , et al., 1996) and Ta is the ambient air temperature ($^oC$).

Energy flux absorbed by the body (ERF) can be equated to longwave emissivity/absorptivity ($\alpha_{LW}$), which is typically equal to 0.95, times additional amount of longwave flux ($ERF_{solar}$). Another result of $E_{solar}$, is the shortwave solar radiant flux on the body surface (W/m$^2$) times shortwave absorptivity ($\alpha_{SW}$), that can be computed based on skin color and clothing as per Table 4.1.

$$\alpha_{LW}\, ERF_{solar} = \alpha_{SW}\, E_{solar} \tag{3}$$

**Table 4.1: Shortwave absorptivity ($\alpha_{SW}$) values for common clothing and skin types (Huizenga, et al., 2001)**

| | White clothing | Khaki clothing | Black clothing | White skin | Brown skin | Black skin |
|---|---|---|---|---|---|---|
| $\alpha_{SW}$ | 0.2 | 0.57 | 0.88 | 0.57 | 0.65 | 0.84 |

$E_{solar}$ is the sum of three fluxes that have been filtered by urban geometry and are distributed on pedestrian body surface (Figure 4.23): direct beam solar energy coming directly from sun ($E_{dir}$), diffuse solar energy from sky vault ($E_{diff}$) and solar energy reflected upward from the floor ($E_{ref}$):

$$E_{solar} = E_{diff} + E_{dir} + E_{ref} \tag{4}$$

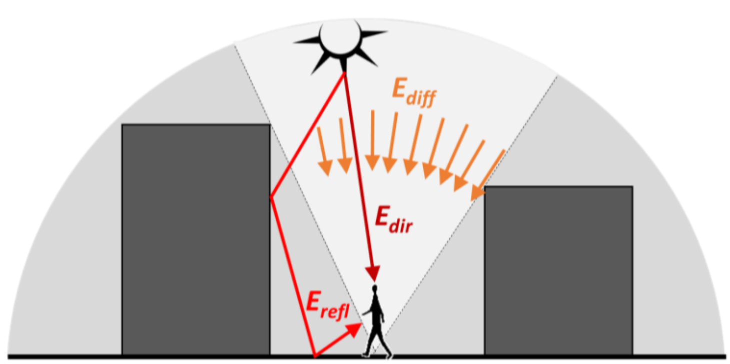



**Figure 4.23: Sum of solar fluxes filtered by urban geometry**

Diffuse solar radiation from the sky is assumed to be distributed on the upper half of exposed portion of the body:

$$E_{diff} = 0.5\, \boldsymbol{f}_{eff}\ (SVF)\ T_{sol}\, I_{diff} \tag{5}$$

Where $\boldsymbol{f}_{eff}$ is the body fraction exposed to radiation, which in case of standing posture is equivalent to 0.725. SVF is the sky view factor, $T_{sol}$ is total solar transmission, which in case of an outdoor setting is equivalent to 1 (unfiltered full transmission) and $I_{diff}$ is the diffuse sky irradiance on horizontal surface (W/m$^2$).

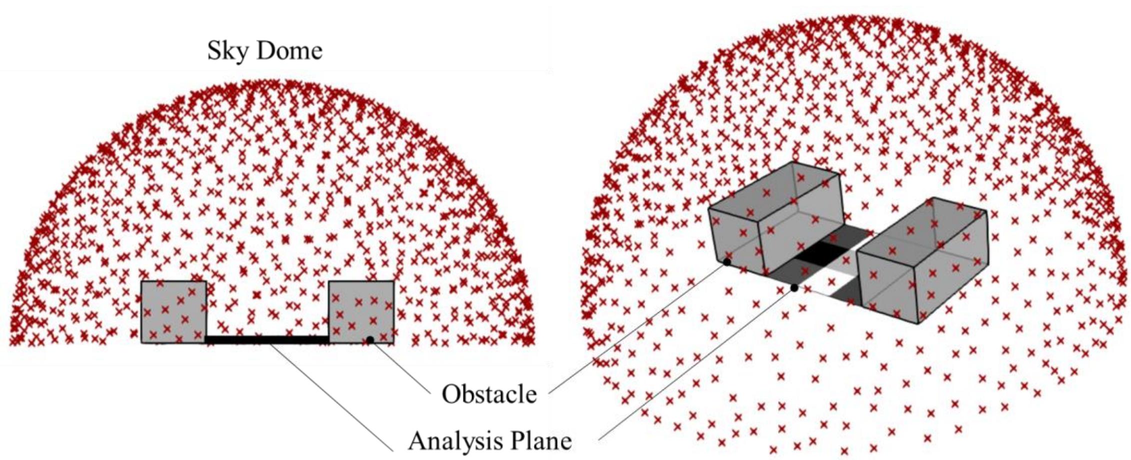



**Figure 4.24: Sky View Factor (SVF) geometric computation**

Sky View Factor (SVF) refers to the ratio of the radiation emitted by the entire hemispheric environment. SVF is typically represented by dimensionless value between 0 and 1, where 0 indicates the sky is completely obstructed by obstacles and 1 indicated there are no obstructions at all. Currently there are multiple tools available for computing SVF, such as: SkyHelios tool developed by Matzarakis (Matzarakis & Matuschek, 2011), SOLWEIG (SOlar and LongWave Environmental Irradiance Geometry model) (Lindberg, et al., 2018), 3D vector processing in tools like ENVI-met and HURES (Park & Tuller, 2014) and Rayman software (Matzarakis, 2012). However, for this thesis a simple method is used for computing SVF, which is by subdividing the analysis surface into points and computing SVF for each point based on the amount of visible sky dome (Figure 4.24).

Direct solar energy is affected only by projected area of the body and is reduced by the impact of shading on the body:

$$E_{dir} = (A_p/A_D)\, \boldsymbol{f}_{bes}\, T_{sol}\, I_{dir} \tag{6}$$

Where $A_p$ is the projected area of a person exposed to direct sunlight; $A_D$ is the DuBois surface area of the assumed person (around 1.8 $m^2$); $\boldsymbol{f}_{bes}$ is the fraction of body exposed to sunlight (not including body's self-shading); and $I_{dir}$ is direct normal solar radiation ($W/m^2$). The metrological radiation parameters can be related as: $I_{TH} = I_{dir} \sin \beta + I_{diff}$, where $\beta$ is the solar altitude.

Geographic location represented in latitude and longitude along with analysis period, are translated using C# code in Grasshopper environment into geometric representation of sun ray, where each ray represents one analysis hour. Based on generated sun rays, obstacle geometry and defined analysis surface: solar altitude $\beta$, incident angle on obstacle geometry, and $\boldsymbol{f}_{bes}$ of each analysis point on analysis surface are computed (Figure 4.25).

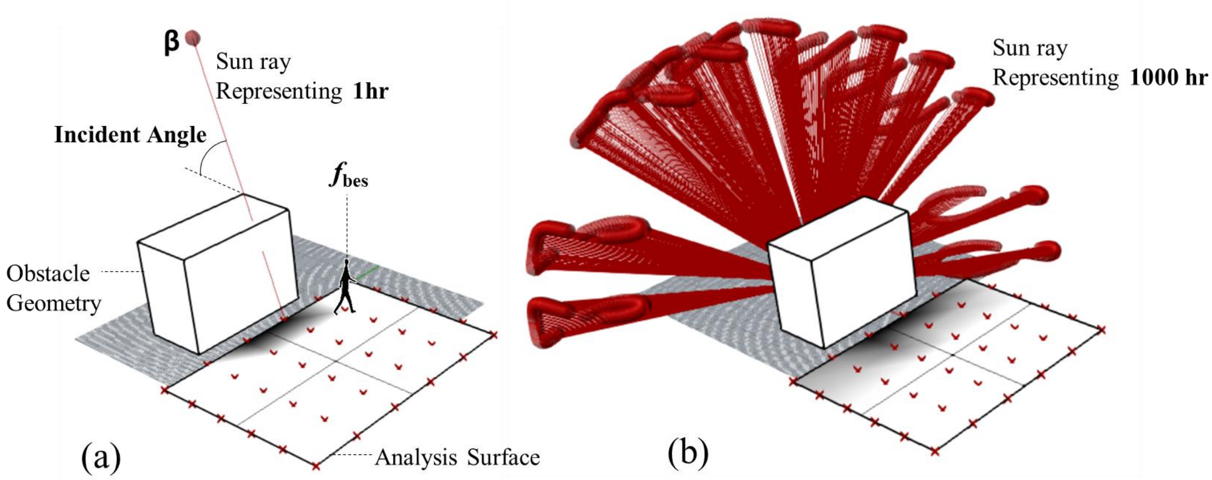



**Figure 4.25: Method of geometrically extracting solar altitude, incident angle and $f_{bes}$ for (a) 1 analysis hour, (b) 1000 analysis hours**

Reflected solar radiation is the short-wave radiation ground-reflected to the lower half of the body, accompanied by increased long-wave radiation from floor surfaces warmed by the non-reflected (i.e. absorbed) portion of the solar radiation:

$$E_{refl} = 0.5\, f_{eff}\ (SVF)\ T_{sol}\, I_{TH}\, R_{floor} \tag{7}$$

Where $I_{TH}$ is the outdoor total horizontal direct and diffuse irradiance (W/m$^2$); and $R_{floor}$ is the floor reflectance (can be represented by shortwave and long-wave radiation combined (0.2 + 0.3).

$ERF_{solar}$ can therefore be calculated using the following equation:

$$ERF_{solar} = (0.5\, f_{eff}\ (SVF)\ (I_{diff} + I_{TH}\, R_{floor}) + A_p\, f_{bes}\, I_{dir} / A_D\,)\ T_{sol}\, (\alpha_{SW} / \alpha_{LW}) \tag{8}$$

By substituting equation 8 in equation 1, MRT can be computed based on location in outdoor space and time of day. The computed MRT can then be used for Universal Thermal Climate Index (UTCI), which is a non-occupational hygiene index to assess heat stress in an outdoor thermal environment for public health purposes (Langner, et al., 2013; Blazejczyk, et al., 2012).

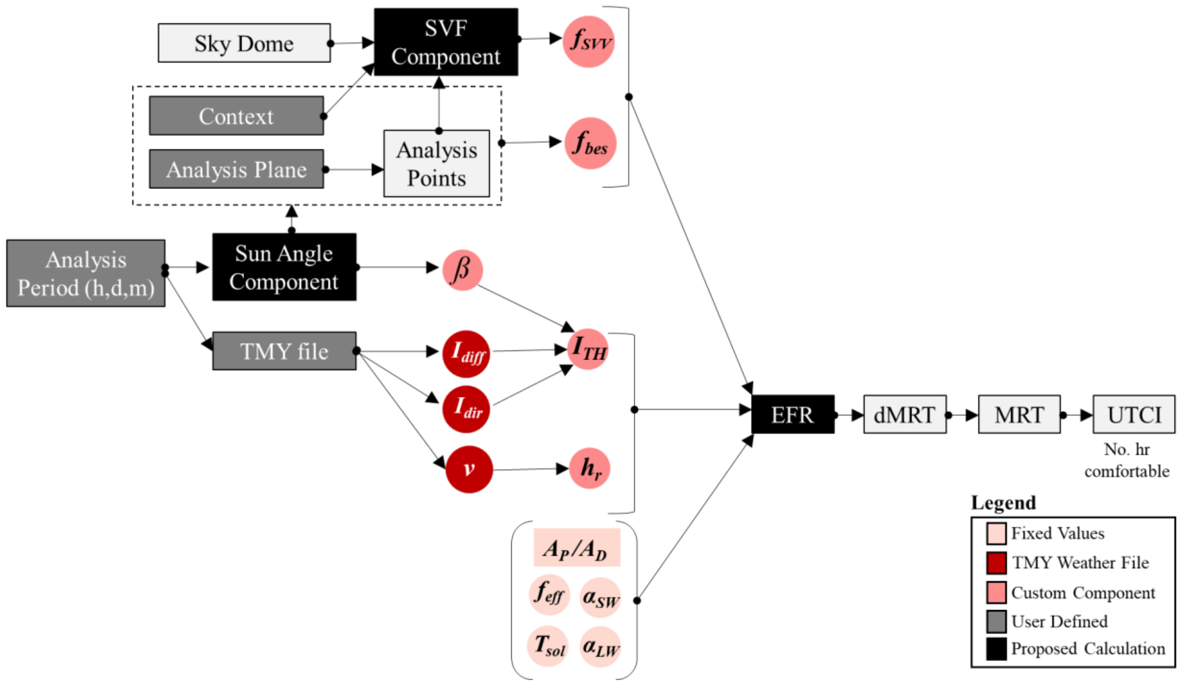



**Figure 4.26: Outdoor thermal comfort calculation method**

The proposed model is a normative model that computes an increase in MRT equivalent to shortwave gains from direct, diffuse and reflected radiation on a person, which is then used to compute UTCI. In order to confirm that the proposed model can adequately support the comparative analysis of outdoor thermal comfort for different variants, it needs to be compared to a validated, and typically higher fidelity model. This validation is conducted below. The chosen model for validation is Ladybug, which is an environmental design plugin for Rhino/Grasshopper and has components for computing MRT and outdoor thermal comfort (Roudsari & Pak , 2013). A simple urban canyon case study is setup to compare the proposed simplified model with Ladybug MRT results. The urban canyon analysis plane is subdivided into 8 analysis points, for which MRT is computed from

8:00am to 4:00pm throughout year in climate condition of Muscat, Oman. It is evident from comparison of the two models that in extreme heat condition, the proposed model overestimates the MRT as compared to the Ladybug model (Figure 4.27). However direct comparison of the outcomes of the two methods is not sufficient. The two models need to be studied under the condition of its true intent, i.e. the relative ranking of outdoor space variants against each other.

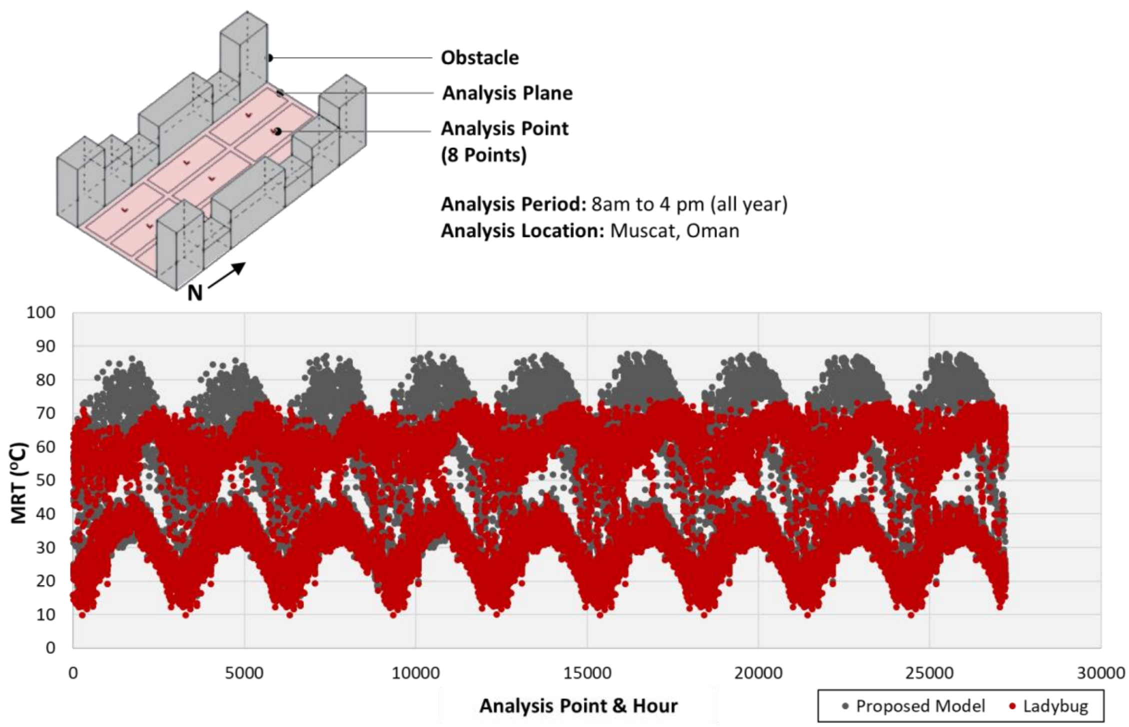



**Figure 4.27: Comparison between proposed model and Ladybug MRT results**

For the comparison of ranking, the Wilcoxon signed-ranks test is used, which is a nonparametric test comparing two sets of ranks that come from the same participators which determines statistically whether the sets of ranks are significantly different (Kim, et al., 2013).

First however, to verify whether two different calculation methods result in two similar rankings of the same variants, we need to generate a set of meaningful and consistent variants to use in the test. For this purpose, the percentages of generic outdoor space are analyzed in a regression model. For setting design variants, generic urban forms based on Martin and March are used (Figure 4.28) with different outdoor space analysis points.

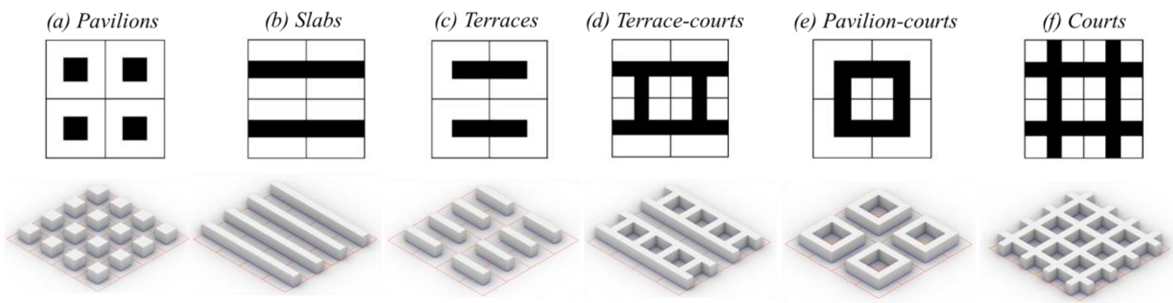



**Figure 4.28: Generic urban forms based on Martin and March (Martin & March, 1972)**

It should not be forgotten that the role of the proposed normative model is not to predict the physical (or "raw") outcomes accurately (which in this case is MRT), but to produce outcome rankings that are objectively correct. Our emphasis therefore shifts to comparing the rankings rather than absolute outcomes.

Furthermore, the comparative analysis should be based on outcomes that are true criteria of the functional performance of the open space.

In this case, to verify whether the two different calculation methods results in comparable rankings across the variant, the percentage of time for which analysis point is within comfort zone is used as the performance criterion to rank design variants. Different analysis points are selected in the generic urban forms by Martin and March, for comparison of the two rankings (Figure 4.29). Let *N* be the sample size, which in this case is the number of analysis points, thus there are a total of $2N$ data points. For pairs $i = 1, \ldots N$, let $x_{1,i}$ denote percentage of comfortable hours computed in Ladybug component and let $x_{2,i}$ denote computation using proposed normative model. There are two hypothesis:

**H$_0$**: difference between the pairs follows symmetric distribution around zero.

**H$_1$**: difference between the pairs does not follow a symmetric distribution around zero.

For $i = 1, \ldots N$, $|x_{2,i} - x_{1,i}|$ and $sgn(x_{2,i} - x_{1,i})$ are calculated, where *sgn* is an odd mathematical function that extracts the sign of a real number. Pairs with $|x_{2,i} - x_{1,i}| = 0$ are excluded and $N$r is reduced sample size. The remaining $N$r pairs are ranked from smallest absolute difference to largest difference $|x_{2,i} - x_{1,i}|$ and let $R$i denote the rank. Test statistic $W$ is calculated $W = \sum_{-1=1}^{N_r} [sgn(, x_{2,i} - x_{1,i}). R_i]$, which is the sum of the signed ranks. Under the null hypothesis, W follows specific distribution with no simple expression. This distribution has an expected value of 0 and a variance of $\frac{N_r(N+1)(2N_r+1)}{6}$ . $W$ is compared to a compared to a critical value from a reference table (Appendix B). The two-sided test consists in rejecting $H_0$ if $|W| > W_{creitical,Nr}$. As Nr increases, the sampling distribution of $W$ converges to normal distribution. Thus, for $N_r \geq 20$, a z-score can be calculated as $z = \frac{w}{\sigma_w}$, where $\sigma_w = \sqrt{\frac{N_r(N_r+1)(2N_r+1)}{6}}$. If $z_{critical} < |z|$, $H_0$ is rejected, else $H_0$ is accepted and two medians are the same.

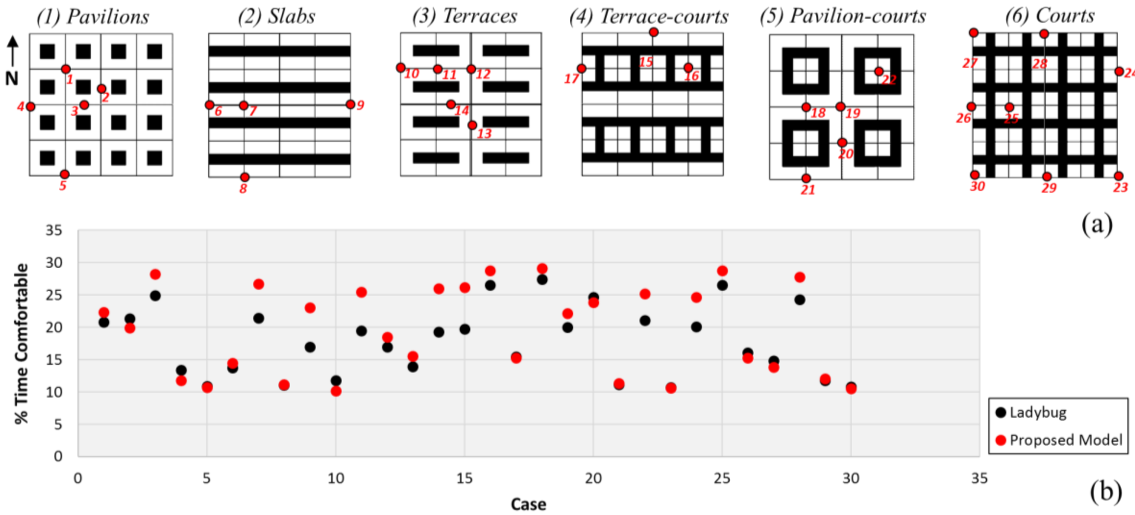



**Figure 4.29: (a) Analysis points in generic urban forms, (b) Comparison between proposed model and Ladybug percentage of time comfortable results**

In Figure 4.30, percentage of time that is found comfortable by normative calculation (vertical axis) and from dynamic simulation (the horizontal axis) is plotted for 150 different cases. The linear regression has $R^2$ of 90.97% indicating that the two sets of outcomes are highly correlated. The actual difference between the two calculation methods falls well within the range of 20% for all cases.

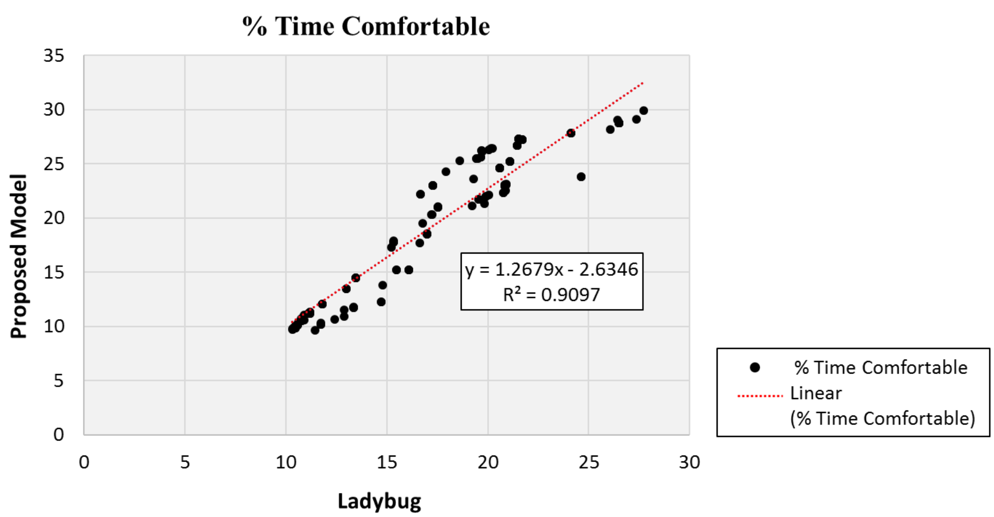



**Figure 4.30: Scatter plot of percentage of time comfortable**

#### 4.4.3.3 PM-3: Application

Performance measure-3 uses two inputs from the urban fabric generation process, which are: “land use allocation”, as open space is allocated at this stage and “building footprint”. Open space is covered by analysis points and the outcome is computed for each point in this analysis grid. In addition to the inputs from the urban fabric generation process, location specific climate data is needed for outdoor thermal comfort measure computation (Figure 4.31).

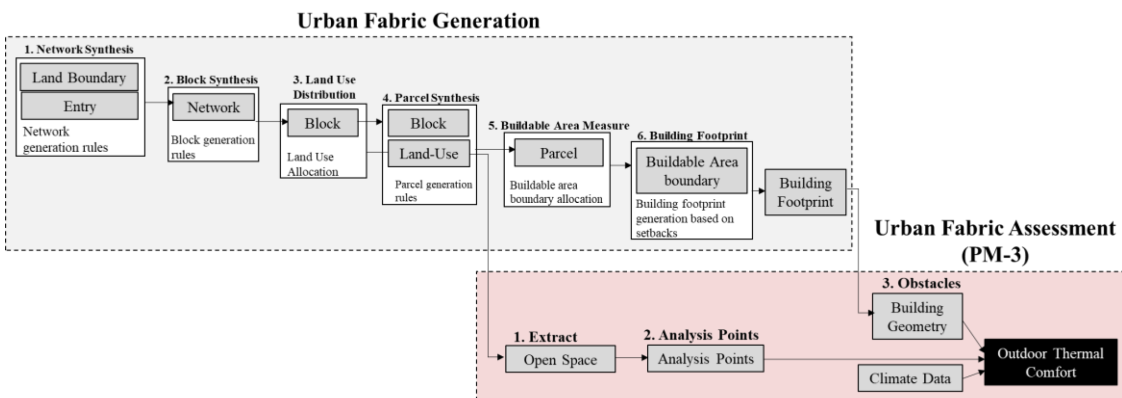



**Figure 4.31: Proposed framework for urban fabric assessment (PM-3) integrated with generation process**

The proposed model for outdoor thermal comfort is used in case studies to evaluate its impact on early decision making, taking design uncertainty into consideration.

In the example shown in Figure 4.32, the decision moment is at the time of land use allocation. The outdoor thermal comfort potential of public outdoor space is evaluated. Three different land allocation options are simulated while uncertainty in building geometry (width, depth, height) is propagated. It is noted that option 1 and 2 have similar percentage of comfortable hours in the given analysis period, whereas option 3 has the possibility of achieving a higher percentage of comfortable hours, albeit that this option, results in a large variance of the computed measure. This is clearly due to the design uncertainty in building geometry, showing that the outcome will be greatly affected by the later design choices of building geometry, which is not the case for options 1 and 2. An additional simulation was carried out to investigate the impact of fully shading the open space, which shows that this will have a probability of achieving more than 33.3% of comfortable hours. Option 3 also has the potential of exceeding 33.3% of comfortable hours, by the suitable selection of building geometry.

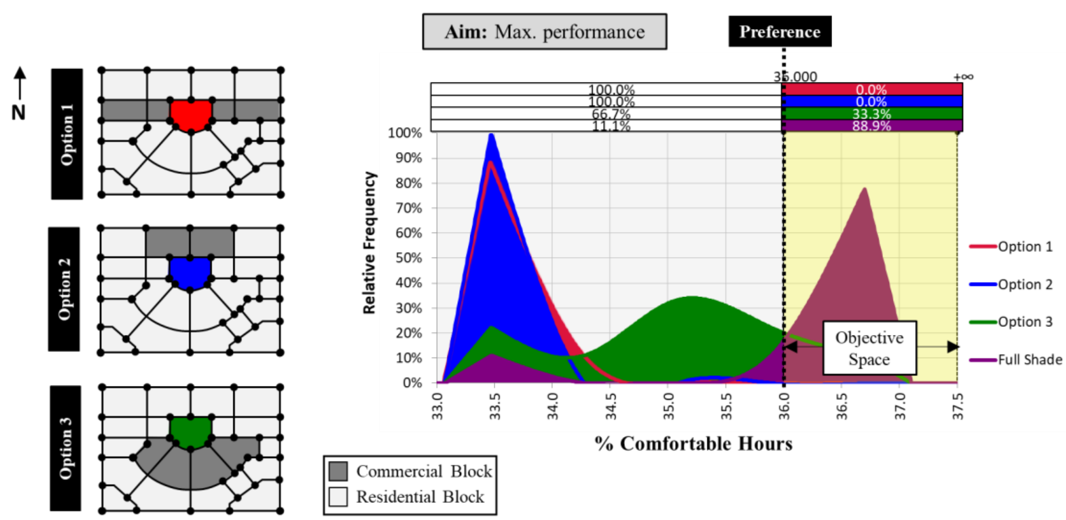



**Figure 4.32: Performance measure -3 for different land allocation options**

Another example is presented in Figure 4.33, where three different urban forms are compared based on the outdoor thermal comfort measure, along with an option that fully shades the outdoor space. From these options, option 2 and 3 has the most potential of attaining a high percentage of comfortable hours as compared to options 1. In fact, with proper selection of building geometry design parameters, the open space in option 2 and 3 can perform as well as a fully shaded open space.

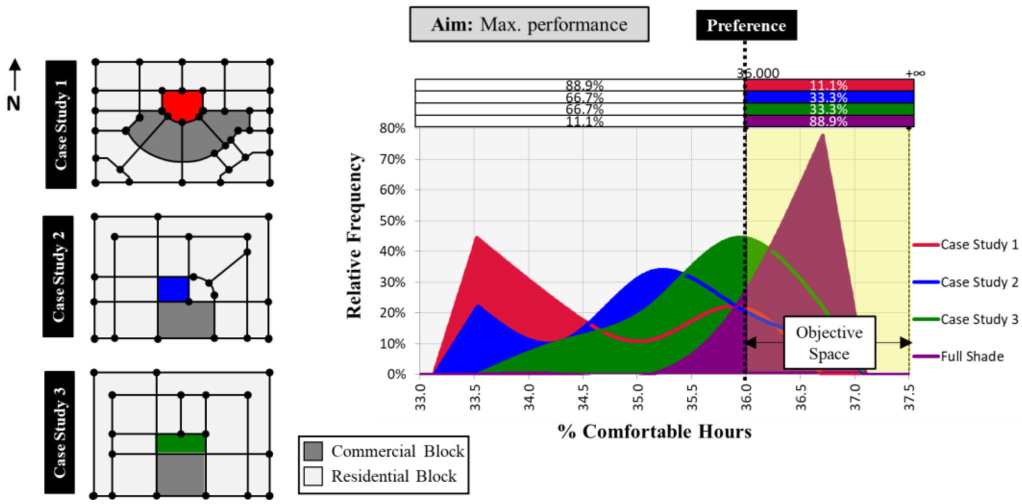



**Figure 4.33: Performance measure -3 for different urban fabric options**

Location and size of open space, building geometry, hence land use allocation (as building geometry is determined by building use) have high impact on outdoor thermal comfort measure. Most high-resolution tools primarily assist in predicting outdoor thermal comfort at the end of the design process, after all crucial design decisions have been made. The problem with that is that it is difficult to comprehend which parameters have the most contribution in the final performance outcome. Taking design parameter uncertainty at different decision points into consideration, allows the designers to foresee the impact of their decisions on the performance outcome range and probability of achieving set target. In doing so, it becomes apparent that the current toolset requires too much detail information that is not available and, in many cases, irrelevant at a given decision moment. This is where the usefulness of a normative toolset based on a granular and reduced order model is immediately obvious. Their inherent simplicity and flexibility are absent in high resolution models which focus on accurate results for fully defined cases, at the expense of more elaborate preparation and longer run times. In addition, the repeated argument is that in early design there is need for comparative analysis of different options rather than accurate performance predictions.

### *4.4.4 Performance Measure-4: Daylight*

#### 4.4.4.1 PM-4: Background

There are many reasons to daylight buildings, both subjective and objective. Measurable aspects such as energy savings, light quality and environmental benefits of daylighting in buildings are undisputed. There are other unmeasurable benefits of daylight, as its rhythms are fundamental to life. Light resets our biological clocks every day and plays a role in many human biological and psychological processes (DeKay, 2010).

Increasing levels of urbanization lead to densification of cities, which has negative consequence on the amount of daylight in buildings. This is often due to the fact that the design in the early stage does not include procedures for evaluating daylight availability in building. The phrase “daylight availability” refers to the amount of light from the sun and sky at a specific location, time, date, and sky condition (Muhs, 2000). Traditional building daylight simulation research has mainly focused on individual buildings and the evaluation tools delivered by these research efforts tend to require extended calculation times for daylight analysis. In order to introduce daylight evaluation as a performance criterion in early design, simulation speed and design parameter detail level are key requirements for implementing it within the design workflow. The importance of implementing daylight evaluation in the urban design phase is motivated by the impact of design decisions at this stage, such as building proportions and set backs on solar and daylight potential of individual buildings (Dogan, et al., 2012).

Daylight performance on the one hand is the result of a series of reductions of daylight access and on the other, an increase of light through reflections. The reduction of daylight in the interior can be described as a situation in which the sky is obstructed by the façade, neighboring buildings and interior partitions, whereas exterior daylight performance is primarily influenced by the street, profile properties, distance between buildings and their heights. The loss of daylight in both cases can be partly compensated by reflections through the texture and color of interior and exterior surfaces (Pont & Haupt, 2009).

Most available daylight design tools are intended to provide information about the levels and distribution of light within a single room. Very few studies address the impact of daylight in the buildings as a whole or in shaping the urban form. On the other hand the studies that investigate the daylight performance at the urban design stage, rely on location specific rules of thumb (DeKay, 2010) or urban spatial attribute correlations (Pont & Haupt, 2009) as shown in Figure 4.34. If we map these daylight design methodologies on a design process timeline, we find that rules of thumb and spatial correlations give general but not quantifiable guidance in a design approach, whereas daylight simulation tools mostly provide an accurate analysis for fully developed building envelopes. In both cases there is not enough assistance provided in early design decision making.

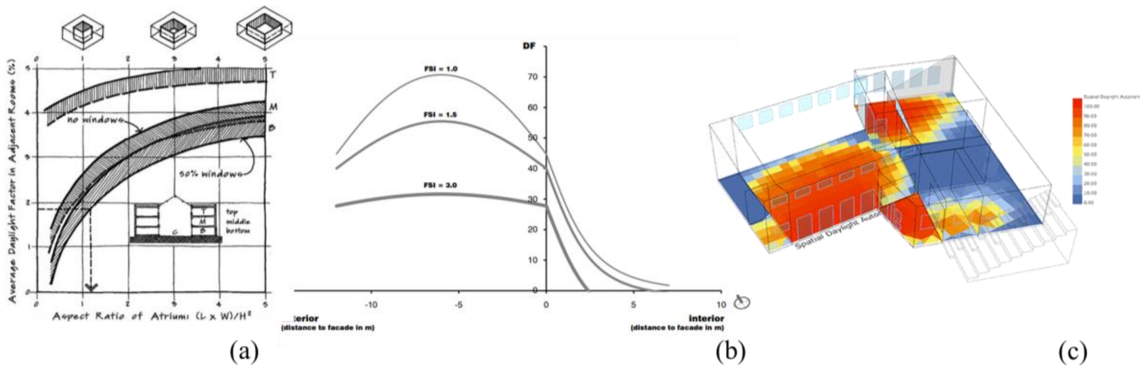


**Figure 4.34: (a) Sizing atria for daylight in adjacent rooms (DeKay, 2010), (b) Daylight Factor (DF) for three sections in which the street width and GSI remain constant (Pont & Haupt, 2009), (c) Daylight analysis using Honeybee extension for Rhino plugin, Grasshopper.**

In order for daylight performance evaluation to be useful in early design, it needs to provide quantifiable and robust results for indoor daylight condition, taking both urban context and building form into consideration.

#### 4.4.4.2 <u>PM-4: Calculation Methodology</u>

Quantity and quality of daylight are variable related to the geographical, meteorological data such as the altitude of the region, turbidity of atmosphere, as well as time (Kandilli & Ulgen, 2008). As buildings are architectural elements that are exposed to sun, a dynamic prediction of daylight availability in them is required. The availability of daylight for exterior illuminance is a field of study considerably different from the measurement and simulation of solar radiation (Robbins, 1986). Solar radiation is defined as total incident energy (visible and invisible) from the sun, whereas daylight is the visible portion of this electromagnetic radiation as perceived by the eye. The aim is to isolate this portion from the total energy. Based on established models, it is possible to predict Luminous Efficacy and estimate the monthly mean of hourly exterior illuminance (diffuse, direct and global) on the horizontal roof and all four facades (N, S, E, W) of any building in a region (Joshi, et al., 2007).

Many researches have investigated the relation between solar radiation and daylight and proposed mathematical models relating the two (Littlefair, 1985; Littlefair, 1988). This requires accurate simulation models of direct and diffuse radiation received from different parts of the sky. Amongst these models, the Perez model is usually considered to be most accurate (Perez, et al., 1990). According to this model, the global ($K_g$) and diffuse ($K_d$) efficacies can be calculated using the following equation:

$$K_g \text{ or } K_d = a_i + b_i\, w + c_i \cos(z) + d_i \ln(\Delta) \quad (9)$$

Where $a_i$, $b_i$, $c_i$ and di are given coefficients (for diffuse or global efficacies), Table 4.2 shows the value of these coefficients corresponding to classification of sky clearness (ε). Δ is sky brightness and *w* is the atmospheric perceptible water content.

**Table 4.2: Luminous efficacy coefficients (Perez, et al., 1990)**

| S No. | ε′ | | Global efficacy coefficients | | | | Diffuse efficacy coefficients | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Lower bound | Upper bound | $a_i$ | $b_i$ | $c_I$ | $d_i$ | $a_i$ | $b_i$ | $c_I$ | $d_I$ |
| 1. | 1 | 1.065 | 96.63 | −0.47 | 11.50 | −9.16 | 97.24 | −0.46 | 12.00 | −8.91 |
| 2. | 1.065 | 1.230 | 107.54 | 0.79 | 1.79 | −1.19 | 107.22 | 1.15 | 0.59 | −3.95 |
| 3. | 1.230 | 1.500 | 98.73 | 0.70 | 4.40 | −6.95 | 104.97 | 2.96 | −5.53 | −8.77 |
| 4. | 1.500 | 1.950 | 92.72 | 0.56 | 8.36 | −8.31 | 102.39 | 5.59 | −13.95 | −13.90 |
| 5. | 1.950 | 2.800 | 86.73 | 0.98 | 7.10 | −10.94 | 100.71 | 5.94 | −22.75 | −23.74 |
| 6. | 2.800 | 4.500 | 88.34 | 1.39 | 6.06 | −7.60 | 106.42 | 3.83 | −36.15 | −28.83 |
| 7. | 4.500 | 6.200 | 78.63 | 1.47 | 4.93 | −11.37 | 141.88 | 1.90 | −53.24 | −14.03 |
| 8. | 6.200 | — | 99.65 | 1.86 | −4.46 | −3.15 | 152.23 | 0.35 | −45.27 | −7.98 |

The sky clearness (ε) for irradiance is given by:

$$\varepsilon = [(I_d + I_n)/ I_d + k\, z^3] / [1 + k\, z^3] \tag{10}$$

Where $I_d$ is the diffuse irradiance, $I_n$ is the normal irradiance; $z$ is the solar zenith angle in radians and $k$ is constant equal to 1.041.

The atmospheric perceptible water content (cm), is given by Wright et al (Wright, et al., 1989):

$$w = \exp\,(0.07\, T_d - 0.075) \tag{11}$$

The sky brightness (Δ) is given by:

$$\Delta = I_d\, m/I_{on} \tag{12}$$

Where $m$ is the optical air mass; Ion is the extraterrestrial normal incidence irradiance. Kasten's (Kasten, 1993) formula was used to obtain $m$, which provides an accuracy of 99.6% for zenith angles up to 89$^o$.

$$m = [\cos z + 0.15(93.885 - z)^{-1.253}]^{-1} \tag{13}$$

The extraterrestrial normal incidence irradiance $I_{on}$ can be calculated by:

$$I_{on} = 1367\, [1.0 + 0.033 \cos(360\, n / 365)] \tag{14}$$

Where $n$ is the day of the year given for each analysis time step. The horizontal diffuse illuminance ($E_d$) and the horizontal global illuminance ($E_g$) can be estimated by the following equations:

$$E_d = I_d\ K_d \quad (15)$$

$$E_d = I_d\ K_d \quad (16)$$

Thus, based on equations (9)-(16), the luminous efficacy and horizontal diffuse and global illuminance can be estimated for any geographic location. Muneer's proposed model for solar radiance (Muneer, 1990), which distinguishes surfaces in the shade from sunlit surfaces. Where the slope is in shade, the illuminance is modelled as a function of the horizontal diffuse illuminance:

$$TF = \{\cos 2(\beta/2) + [2b/\ \pi(3 + 2b)]\ (\sin(\beta) - \beta \cos(\beta) - \pi \sin^2(\beta/2))\} \quad (17)$$

Where $TF$ is defined as the tilt factor, β is the surface (façade) slope and b is the radiance distribution index introduced by Moon and Spencer (Moon & Spencer, 1942). For a shaded surface (b=5.73), for sunlit surface under overcast sky (b=1.68) and for sunlit surface under non-overcast sky (b=-0.62). The proposed model by Muneer (Muneer , 1993) incorporates three components which when combined give a full representation of the sky hemisphere. These are the beam component, an isotropic background diffuse component and a circumsolar component, corresponding respectively to the three terms in the following equation:

$$E_\beta = (\cos i\ /\ \sin \alpha)(E_g - E_d) + E_d\ [(1\text{-}F)TF] + E_d\ [F\ (\cos i\ /\ \sin \alpha)] \quad (18)$$

Where $i$ is the incident angle on the façade (Figure 4.25), α is the azimuth angle and F is clearness function sensitive to seasonal changes, given by the following equation:

$$F = (E_g - E_d)/E_o \tag{19}$$

$E_o$ is mean extraterrestrial normal illuminance and is equal to 133.8 klux (Joshi, et al., 2007). The interior illuminance can be predicted by the following equation:

$$E_i = (A_g E_\beta \tau \rho)/A_f \tag{20}$$

Where $E_i$ is illuminance level inside the space on horizontal working surface, $A_g$ is total area of glazing, $\tau$ is transmittance of glazing, $\rho$ is average reflectance of all room surfaces and $A_f$ is floor area. The calculation workflow for predicting the illuminance level is shown in Figure 4.35.

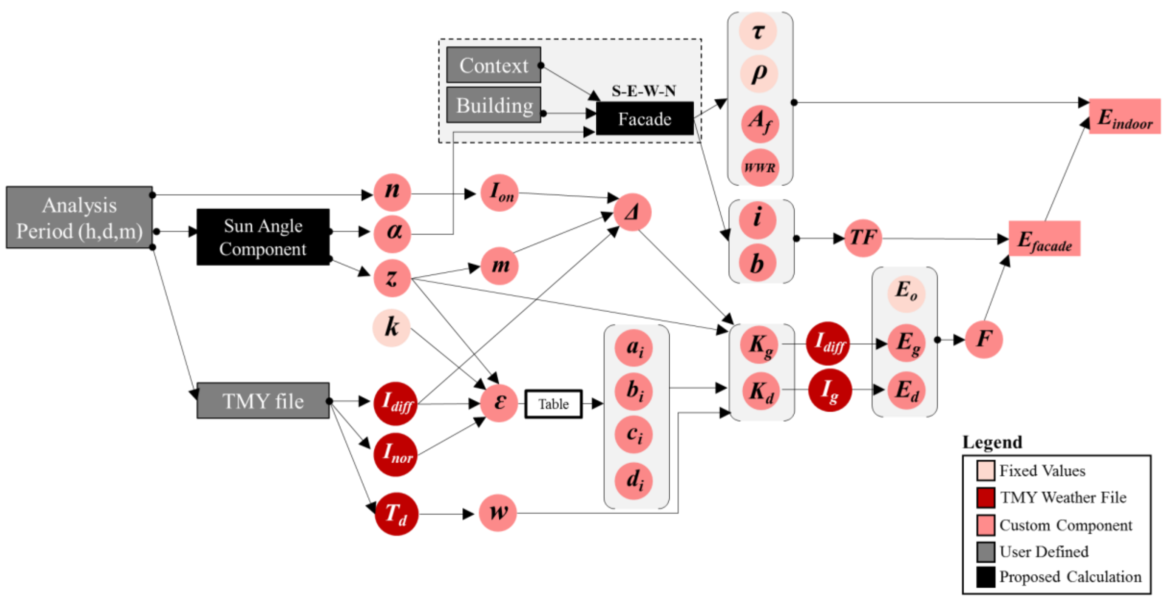



**Figure 4.35: Indoor illuminance calculation method**

According to the IES Daylight Metrics Committee, a location in space is considered "daylit" if the illuminance due to daylight is above 300 lux for half of the occupied time in the year, which is nominally considered to be daily from 8am to 6pm (Reinhart, et al., 2013). This can be condensed into one a single, meaningful number, which is percentage of occupied time during which indoor illuminance is above 300 lux. If this percentage is more than 50% (the setting of this target is case and client expectation dependent), then the building achieves the minimum target.

The performance measure formulated to check whether the building achieves the target is “percentage of occupied time during which interior illuminance is greater than 300 lux”. The preference is to achieve this could be for instance 50%. The computation of the measure serves to verify that the buildings is sufficiently daylit for the 50% achievement target. This measure does not and should not take into consideration the change that might occur in the interior illuminance because of placement of interior partitions. This is because within the scope of urban design, parameters concerning individual buildings and especially their zonal configuration have not yet been decided upon.

#### 4.4.4.3 PM-4: Application

Performance measure-4 uses only one input from the overall urban fabric generation process, which is “building footprint”, along with location specific climate data (Figure 4.36). Building geometry input is used both as urban context of the building to be analyzed. Geometric properties of each building along with its surrounding context are used to compute its indoor illuminance level (Figure 4.36).

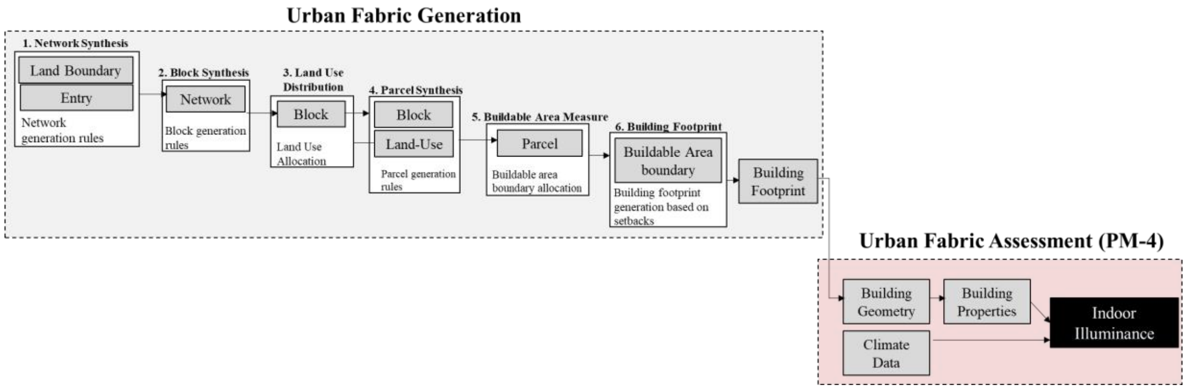



**Figure 4.36: Proposed framework for urban fabric assessment (PM-4) integrated with generation process**

Based on calculation methodology introduced in section 4.4.4.2, indoor illuminance of different building forms in various urban settings based on Martin and March's archetypes can now be computed and compared, changing the window to wall ration to 30% for each of the four facades. It is evident from this comparison (Figure 4.37), that building form and its placement within the urban fabric has fundamental influence on the indoor illuminance level as it impacts sunlight transmitted to interior space. Figure 4.37 shows the urban fabric, building chosen within urban fabric for interior illuminance computation and illuminance level received from each façade. Case (b,d,e) have most illuminance received from South facade as compared to rest of cases as they have least obstructions. Whereas case (f) has least illuminance level because of the building shape and obstructing urban fabric.

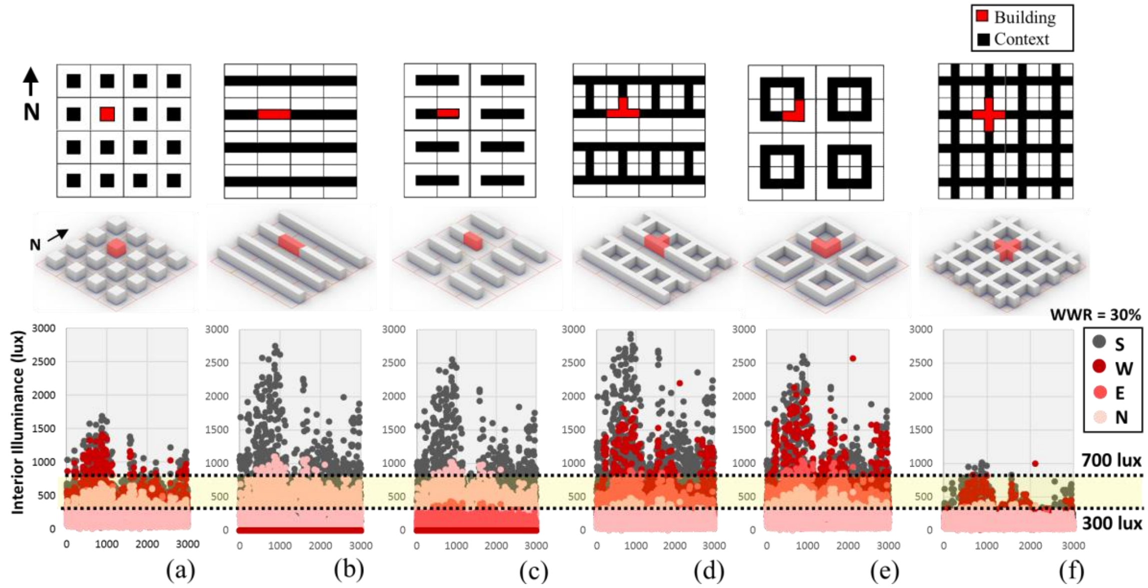



**Figure 4.37: Comparison of interior illuminance level of buildings in different generic urban forms, based on Martin and March archetype (Martin & March, 1972)**

Design parameters that have the greatest impact on indoor daylight of buildings are building setbacks, building geometry and window-to-wall ratio. Urban fabric itself does not impact the daylight performance measure if the mentioned three parameters are constant. In case study shown below (Figure 4.38), two different urban fabrics are compared with similar free-standing building geometry type and identical distribution of setbacks and window to wall ratio. It is noted that the outcome of percentage of time space has an interior illuminance more than 300 lux for half of the occupied time is 42.7% for option 1 and 39.9% for option, which is relatively similar for both urban fabrics. This is due to similar exterior context, geometry and building properties generated for both options, which lead to similar interior daylight condition.

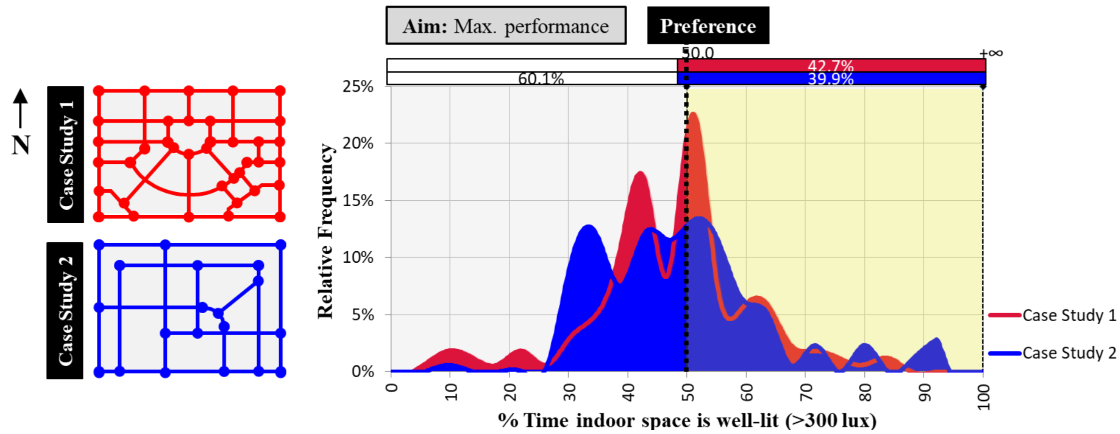



**Figure 4.38: Performance measure -4 for different urban fabric options**

This indicates that the daylight measure is a useful performance measure at the decision point of choosing the building set back, deciding building geometry and determining window-to-wall ratio requirement. However, this performance measure does not provide notable contribution to decision making if mentioned parameters are set equal in the variants that are subject to preference decision.

Let's now look at the case of comparing the impact of different window-to-wall ratio values (their mean and distribution, as shown in Figure 4.39) on the interior daylight outcomes (Figure 4.39). It is noted that option 2 with WWR of 30% as a set preference, has a probability of 89.6% of achieving 300 lux in the interior space for more than half of the occupied time as compared to 47.7% probability of option 1 of achieving the same outcome, WWR preset to 25%. Although option 2 is a clear favorite, as higher WWR would lead to better illuminance levels, quantifying the impact on the outcome is not possible without intensive and elaborated simulations in high resolution tools.

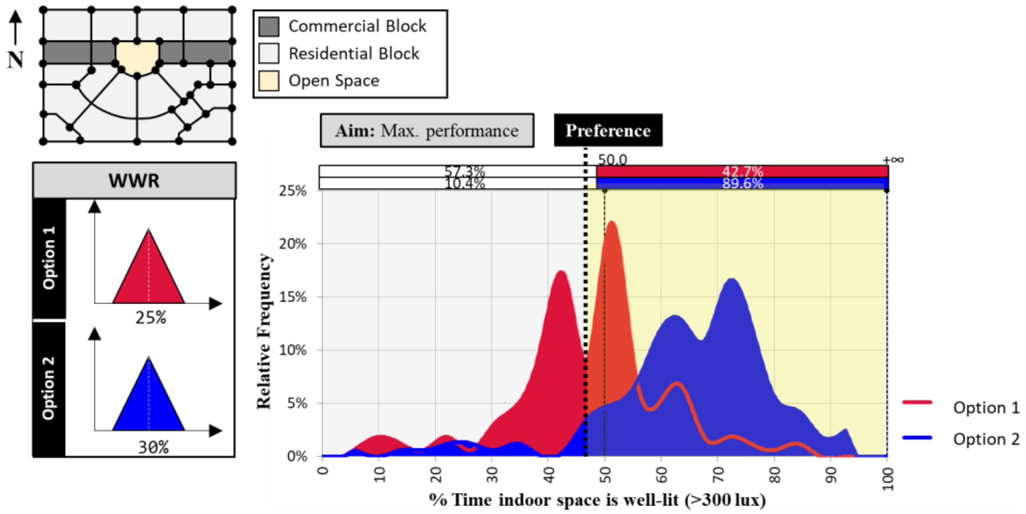



**Figure 4.39: Performance measure -4 for different WWR in the same urban fabric**

In another case, building typology is used to compare between two design options. Outcome of freestanding building typology is compared with row house typology in the same urban fabric. It is noted that option 1, has a probability of 39.9% of achieving the target as compared to 14.7% of option 2, making option 1 an obvious choice.

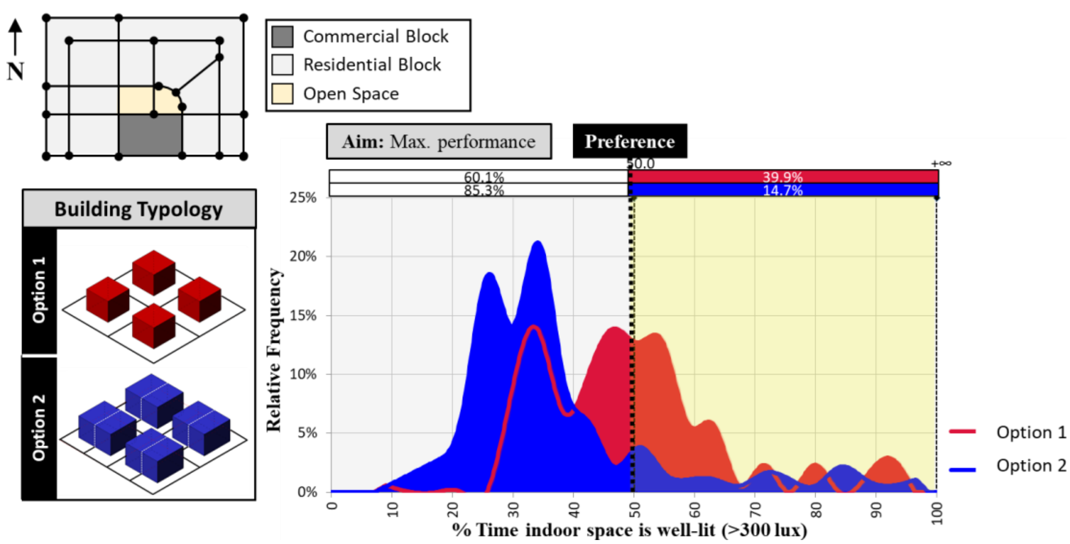



**Figure 4.40: Performance measure -4 for different typology in the same urban fabric**

Although, it is not a surprise that the freestanding typology will lead to higher interior illuminance as compared to row house, as freestanding can receive daylight from all four facades, the outcome is significant because the proposed model reveals the difference between the options in quantified from (mean and distribution). In this case option 1 is 25.2% better than option 2 in achieving the daylight target. As it is established that urban design decision making is multi-objective problem, understanding the impact of choosing one option over the other over different categories, allows the decision maker to make informed tradeoffs leading to more robust design decisions.

### *4.4.5 Performance Measure-5: Urban Building Energy*

#### 4.4.5.1 PM-5: Background

Interaction between urban spatial patterns and energy has been intensively studied especially during the 1970s because of the energy shortage awareness after oil crisis (Alberti, 1999; Beaumont & Keys, 1982). Some researches focused on the impact of land use pattern and spatial structure on urban energy flows (Kalma, et al., 1978; Kalma, et al., 1978), whereas others focused on energy requirements based on human activities (Douglas, 1983; Alberti, 1999). However, few studies tackled impact of urban fabric on energy use. One of the most noted researches in this aspect is that of Newman and Kenworthy (Newman & Kenworthy, 1989) which showed negative correlation between urban density and annual gasoline use per capita (Figure 4.41).

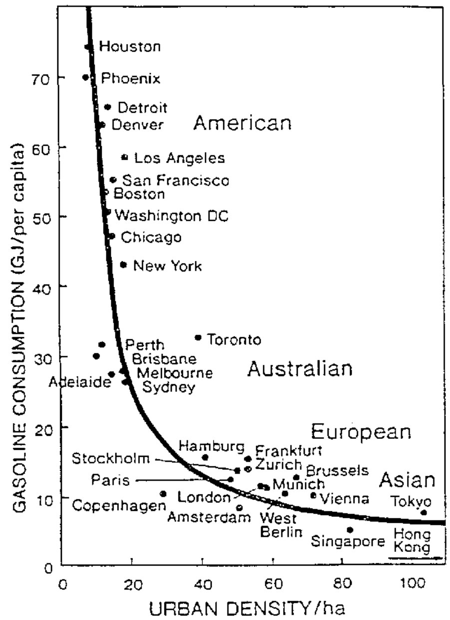



**Figure 4.41: Gasoline use per capita versus population density (1980) (Newman & Kenworthy, 1989)**

Building energy performance is one of the measures of building efficiency and is defined as the regulated energy part of the total building energy consumption, or the cooling and heating load. Building physics understanding is used to create comfortable indoor environment in buildings and calculate required heating and cooling demand of buildings. The outdoor climate varies greatly, hence the separation between indoor and outdoor, which is why the building envelope becomes a critical component in building physics studies. Building geometry, its envelope, function, HVAC systems and occupant behaviors are major influential factors in building energy use. Many researchers investigated the correlation of these factors to building energy use. These studies focused on individual buildings as the traditional unit of analysis, but when the system boundary is extended from the individual building to urban environment, new geometric measures are needed to describe the spatial relationships between buildings and other morphological features of the urban environment. In routine energy simulations, the capture of the outdoor environment in urban settings is mostly simplified to solar position, sky dome luminance, featureless ground and climate (Hensen & Lamberts , 2012). However, the external environment of buildings is not featureless, they consist of buildings, streets, pavements and vegetation. Furthermore, these components have complex interactions with each other, suggesting far more complex environmental variables that impact the system boundary, and are typically translated to the microclimate parameters that act as the boundary conditions at the individual building envelopes.

Some scholars applied tools developed for individual building energy assessment to study building stocks in a neighborhood or in a city, they found notable discrepancy between measured and simulated data (Choudhary, 2012), indicating the impact of urban context. This also suggests that urban buildings may not perform in terms of energy use in the same way as simple aggregation of each building. Some scholars introduce "second-order uncertainty" to account for unknown effects of the urban context (Booth, et al., 2012). However, application of this research results is limited without study of casual relations.

Some researchers noted the influence of urban context on building energy consumption, among them was Ratti et.al. (Ratti & Richens, 2004; Ratti, et al., 2005), who summarized important urban context factors influencing energy performance. However, the individual contributions of these factors were not quantified.

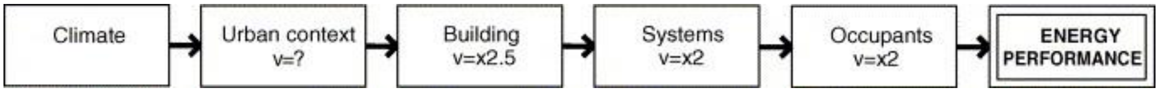



**Figure 4.42: Factors that affect energy consumption in buildings (Ratti, et al., 2005)**

A single building is already a complex system (Al-Homoud, 2001), so a building in an urban context becomes a “system of systems” (Maier, 1998) or the “network of networks” (Batty, 2013). In such system, spatial interactions between buildings impact the energy performance of individual buildings.

Because of the spatial proximity of buildings, solar gain of buildings and microclimate are greatly impacted by neighboring buildings, leading to an impact on building energy consumptions. As solar radiation is the major source of heat gain in buildings, mutual shading by nearby buildings and general proximity in an urban context changes the heat balance of buildings, hence modifying energy use of individual buildings (Olgyay, 1967; Olgyay, 1963). How large this impact is dependent on proximity (density) but also on individual building parameters, mainly orientation and WWR in different façade orientations.

#### 4.4.5.2 PM-5: Calculation Methodology

Most of the building energy consumption occurs during the operational phase. Considering building type and the local climate condition, the major consumers of energy are heating, cooling, lighting and the power consumed by the systems that support the building operation and activities of the occupants. The expected operational energy consumption is determined for the most part envelope decisions during the design phase. It is thus highly desirable that building energy performance is evaluated systematically in the design phase.

A group of CEN-ISO standards has been developed to support the implementation of the European Directive 2002/91/EC on the Energy Performance of Buildings (EPBD).

The standards introduce methods to quantify energy performance with the use of quantified evaluations based on a set of normative calculations. The outcomes of the evaluation are defined at three levels of energy use: (1) thermal energy needs, (2) delivered energy, and (3) primary energy/$CO_2$ emission.

Figure 4.43 illustrates energy flows which are to be calculated by predefined calculation methods in the standards and explanation of calculation nodes is as following (EN-ISO 2017):

**Node [1]**: represents the required energy to fulfill the user's requirements for heating, cooling, lighting, etc. according to levels that are specified for the purpose of calculation.

**Node [2]**: represents the "natural" energy gains-passive solar heating, passive cooling, natural ventilation, day-lighting and internal gains (occupants, lighting, electrical equipment, etc.).

**Node [3]**: represents building's energy needs, obtained from node [1] and node [2] along with the characteristics of the building itself.

**Node [4]**: represents the delivered energy, recorded separately for each energy carrier and inclusive of auxiliary energy, used by space heating, cooling ventilation, domestic hot water and lighting systems, taking into account renewable energy sources and co-generation. This may be expressed in energy units or in units of energy types (kg, $m^3$, kWh, etc.).

**Node [5]**: represents the produced renewable energy on the building premises.

**Node [6]**: represents generated energy, produced on the premises and exported to the market; this can include part of node [5].

**Node [7]**: represents the primary energy usage or $CO_2$ emissions associated with the building.

**Node [8]**: represents the primary energy or $CO_2$ emissions associated with on-site generation which is used on-site and thus is not subtracted from node [7].

**Node [9]**: represents the primary energy or $CO_2$ savings associated with energy exported to the market, which is thus subtracted from node [7].

The overall calculation process involves following the energy flow nodes from the left to right in Figure 4.43 can be grouped according to the procedure of performance-based assessment:

- **Level 1**: Thermal energy needs ($Q_{nd}$) – [1], [2], [3]
- **Level 2**: Delivered energy ($E_{del}$) – [4], [5], [6]
- **Level 3**: (a) Primary energy ($E_p$) and (b) $CO_2$ emissions – [7], [8], [9]

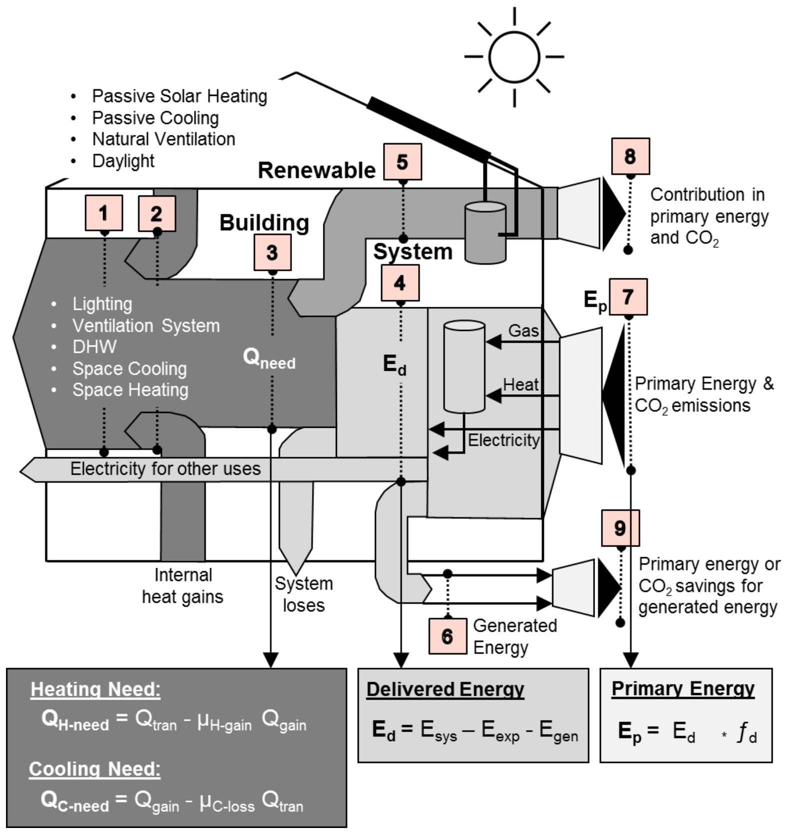



**Figure 4.43: Schematic EPC calculation**

Calculation starts from **level 1**: thermal energy needs ($Q_{nd}$) which takes into account the energy losses (transmission and ventilation, the heat gains (solar, internal and system heat sources), the dynamic parameters (gain and loss utilization factor).

On **level 2**: Delivered energy ($E_{del}$), the required energy for heating, cooling, ventilation, domestic hot water, lighting and auxiliary system is calculated. It is necessary to first calculate the thermal energy needs for heating and cooling systems. The energy requirements of each system are calculated based on the design of the system. Heating and cooling energy losses via water or air delivery and renewable energy generation on site have all been taken into account. The delivered energy corresponds to the total annual delivery to the site by each energy carrier.

In **level 3**: Primary energy ($E_p$) and $CO_2$ emission is calculated based on the calculated delivered energy and weighting factors (primary energy factor and $CO_2$ emission).

For early design decision, the level 1 outcome (building thermal energy need) is most appropriate, as the purpose of calculating the required building thermal energy is to compare the energy performance of various urban design alternatives. Moreover, at the design stage, there is no decision made about HVAC systems, hence the thermal energy need for cooling and heating is ideal for unbiased comparison. EPC reduces the thermal energy need calculation to the essential (reduced order) heat balance without loss of accuracy, hence making it suitable for early design stage estimation in comparison to tools like EnergyPlus, which require a lot more details than can be expected to be available and furthermore uses substantially more run time without benefits for comparative analysis.

The main inputs needed for the calculation are the following:

- Transmission and ventilation properties.
- Heat gains from internal heat sources, solar properties.
- Climate data.
- Description of building and building components, systems and functions.
- Thermal comfort requirements (set-point temperature and ventilation rates).
- Data related to heating, cooling, hot water, and ventilation and lighting systems.

The main outputs of thermal energy need are:

- Aggregated energy required for space heating and cooling.
- Length of heating and cooling season.

Additional, outputs are the following:

- Monthly values of energy requirement and energy use.
- Monthly values of main contributors in the energy balance (transmission, ventilation, internal heat gains, and solar heat).
- Contribution of passive solar gains.
- System losses (from heating, cooling, hot water, ventilation and lighting systems) recovered in the building.

Energy need for space heating and cooling is calculated in each month according to the following:

For heating need:

$$Q_{H,nd} = Q_{ht} - \eta_{H,gn} Q_{gn} \tag{21}$$

$$Q_H(t) = (H_{tr} + H_{ve})(\Theta_{int,set,H} - \Theta_e)t - \eta_{H,gn}(Q_{sol} + Q_{int}) \tag{22}$$

For cooling need:

$$Q_{C,nd} = Q_{gn} - \eta_{C,ls} Q_{ht} \tag{23}$$

$$Q_C(t) = (Q_{sol} + Q_{int}) - \eta_{C,ls} ( H_{tr} - H_{ve})(\Theta_{int,set,C} - \Theta_e)t \tag{24}$$

Where:

| | |
|---|---|
| $Q_H$, $Q_C$ | is the total heating and cooling thermal energy needs in MJ |
| $Q_{ht}$ | is total heat transfer energy, in MJ |
| $Q_{gn}$ | is total heat gain, in MJ |
| $t$ | is the assessment time period, monthly method, in Ms |

$H_{tr}$, $H_{ve}$ is the heat transfer coefficient of the building by transmission and ventilation, W/K

$\Theta_{Int,set,H}$, $\Theta_{int,set,C}$ is the internal set point temperature for heating and cooling, averaged over the building, in $^{o}C$

$\Theta_e$ is the mean external temperature, averaged over the time period, in $^{o}C$

$Q_{sol}$ is the sum of the heat sources from solar sources, in MJ

$Q_{int}$ is the internal heat gains of the whole building, in MJ, including recoverable technical system thermal losses if applicable

$\eta_{H,gn}$, $\eta_{C,ls}$ Is the dimensionless gain and loss utilization factor for heating and cooling

For implementation in the proposed platform, *Rhinoceros* is used as the building geometry modeling platform and *Grasshopper* as carrier for algorithmic definitions. A newly developed EPC component, based on the Grasshopper definition, reads the generated geometry from *Rhino* and computes the performance measure, which is building energy need in this case.

For computing energy need of each building in an urban context, input data is categorized into three parts based on how they are computed (Figure 4.44):

- **Building Geometric Properties**: building geometric properties, such as: envelope surface areas, window-to-wall ratio and orientation are extracted from building model. The building property extraction is linked to the urban fabric generation model, so if there is any change in the shape design parameters, this change is reflected in the building geometric properties.

- **Building Operational System**: each building type is linked to different building operational properties (envelope material, HVAC systems, and internal loads), this building archetype library is based on the local regulations and recommendations of each building type and can be changed as per the project requirements.
- **Surrounding Context**: impact of surrounding urban context on the building shading is computed using SRF component, which will be explained in detail later in this section.

All input data is then used in an EPC-calculator component and the output, which is thermal energy need (cooling need $Q_C$ and heating need $Q_H$,) is stored in an external excel file for each building in the urban fabric. This process repeats for all buildings until all possible urban fabric alternatives are dealt with. Uncertainties enter at this stage for each alternative, i.e. for a subset of the input parameters of the buildings in a given design option that are undecided. In that case the EPC calculator is called for all plausible values of the undecided variables, which results in a probability distribution of EPC calculated outcomes such as urban (aggregated) energy need.

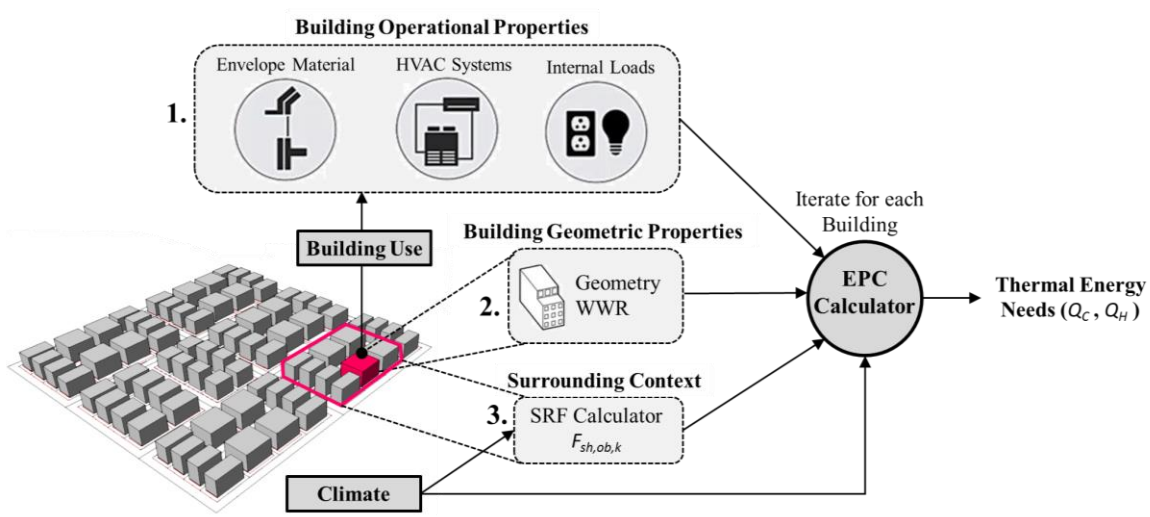



**Figure 4.44: Schematic model for proposed urban energy modeling**

A large portion of the building's energy performance has to do with how it behaves in relation to its environment, and one of the most important aspects of environment is the solar gain: $Q_{sol}$. The sum of the heat gain from solar sources for a monthly calculation is expressed as following:

$$Q_{sol} = (\Sigma_k F_{sh,ob,k} A_{sol,k} I_{sol,k})t \qquad (25)$$

Where:

| | |
|---|---|
| $Q_{sol}$ | is the sum of the heat sources from solar sources, in MJ |
| $F_{sh,ob,k}$ | is the shading reduction factor for external obstacles for the $A_{sol,k}$ |
| $A_{sol,k}$ | is an effective solar collecting area of surface k (glazing and opaque) |
| $I_{sol,k}$ | is the mean solar irradiation during time period on the area $A_{sol,k}$ with a given orientation, in $W/m^2$ |
| t | is the length of the month, in hr |

Climate data can be used to extract $I_{sol,k}$ and t, and building geometry can be used to compute $A_{sol,k}$. However, the shading reduction factor ($F_{sh,ob,k}$) is specific to the urban setting (building arrangement) as it depends on the building's surrounding context. The shading reduction factor is taken as 1 if the surface is fully exposed to sun and is considered 0 if the surface is fully shaded. If we don't take shading of the surrounding context into account, the output of building energy need, primary and delivered will not represent the real scenario, hence cannot be relied upon as representative of actual building performance. Figure 4.45, shows a comparison between energy calculation for two cases, in the first case building surrounding context is not taken into consideration hence the shading reduction factor is set to 1 for all surfaces, whereas in the second case context is taken into account and $F_{sh,ob,k}$ is computed for each building surface. The shading reduction factor is taken as monthly average for each façade and monthly delivered energy is computed for each building. It is evident from the comparison that when shading due to context is not taken into account, the results do not represent the variation that occurs in real contexts and energy consumption is over-estimated and uniform for same size buildings.

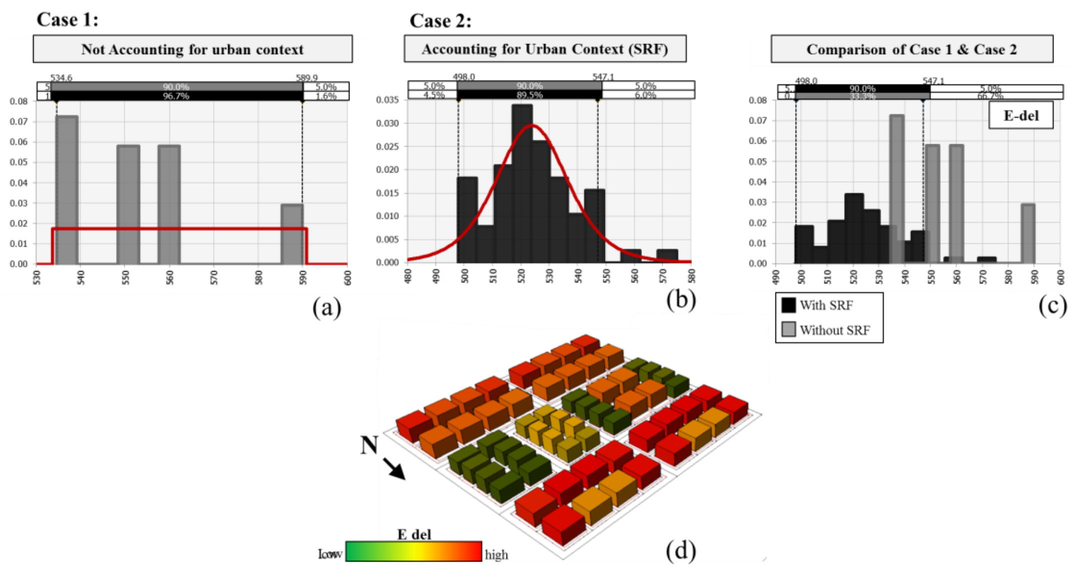



**Figure 4.45: Delivered energy (a) Not accounting for urban context, (b) Accounting for urban context, (c) Comparison of both cases, (d) Variation of outcomes from Case 2.**

In order to compute the shading reduction factor (SRF) there are three important components that we need to take into consideration (Figure 4.46):

- **Rays**: Sun direction rays based on time and location.
- **Surface**: Building surfaces to compute SRF on.
- **Obstruction**: Surrounding context that casts shadow on the building of interest.

The following explains the implementation approach:

A *Sun Angles* component (Grasshopper, 2012) developed in C# is used for computing the direction of the sun on the basis on time and location (latitude and longitude). This C# component calculates the position of the sun at a given day and time of the year, it relies on a simple algorithm to compute the solar angle, which is sufficient to perform needed analysis.

To calculate the SRF, a building is segregated into surfaces in nine orientations (North, North East, East, South East, South, South West, West, North West and Roof). These surfaces are then converted into a mesh. The vertices of the resultant mesh are used to calculate the area of the surfaces which are hidden from the sun by the surrounding context. The proposed setup calculates the amount of sunlight that hit each point of the surfaces without being occluded by the building. To calculate the occlusions, the *Occlusion* component in the native *Grasshopper* components is used, which computes whether or not a point can be seen given a direction and a set of obstruction geometry.

For the obstruction geometry, buildings within a specified radius from the chosen building are included as surrounding context. The results of the calculation is a list of values specifying how many of the provided vectors are able to avoid the obstruction geometry and hit each sample point (of the mesh).

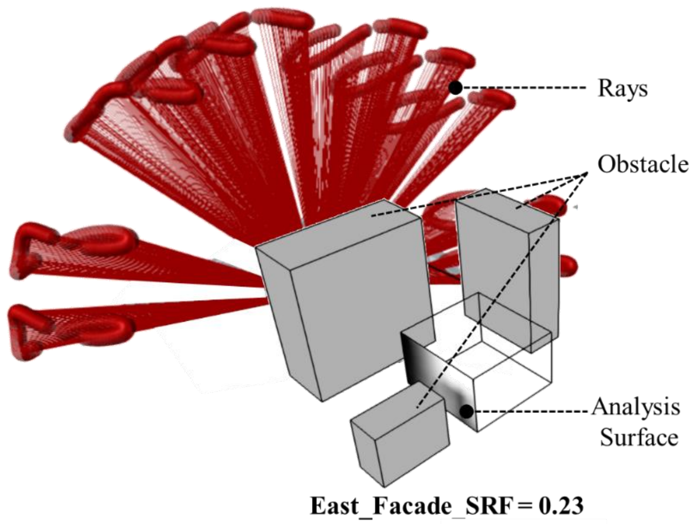



**Figure 4.46: Parameters of shading reduction factor (SRF) component**

4.4.5.3 PM-5: Application

Performance measure-5 uses two inputs from the urban fabric generation process, which are: “Land use”, which is used to extract building operational properties and “building footprint”, which is used both for urban context and buildings to be analyzed. In addition location specific climate data is used as input for the normative energy model to predict building energy use for each building within the generated urban fabric (Figure 4.47).

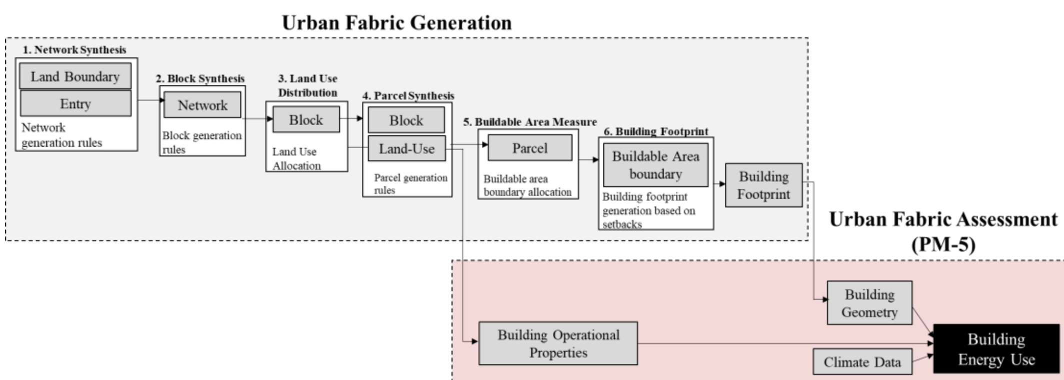



**Figure 4.47: Proposed framework for urban fabric energy assessment (PM-5) integrated with generation process**

The proposed normative urban energy model is used in 2 cases, in the first case the decision point is land allocation within the same urban fabric and the range of design parameter uncertainty of building geometry is specified within small ranges to allow the designer to explore the impact of land allocation while all other parameters are constrained. It is evident from comparing the performance outcome of the three options that option 1 has probability of 88.7% of achieving cooling load less than 150 kWh/m$^2$ as compared to probability of 51.7% for option 2 and 47.9% for option 3, making option 1 a clear choice in terms of performance measure 4.

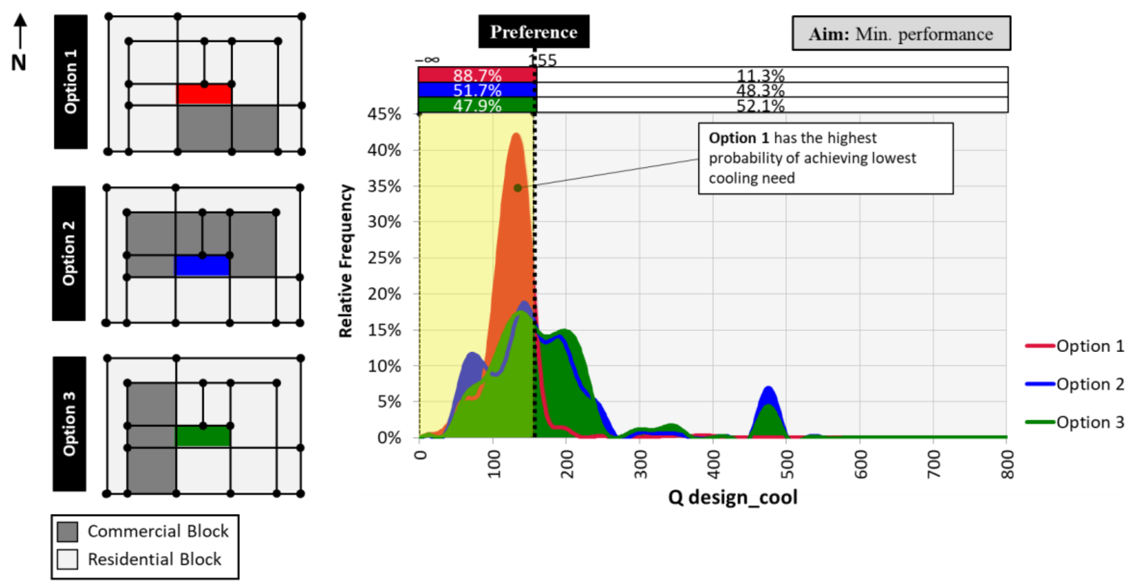



**Figure 4.48 : Performance measure-5 for different land allocations**

In the second case, two different urban fabrics are compared at the land allocation decision point, while keeping building geometry design parameter uncertainty constrained. It can be seen from this comparison that option 1 has probability of 79% of achieving cooling load less than 150 kWh/m$^2$ as compared to probability of 48.6% for option 2.

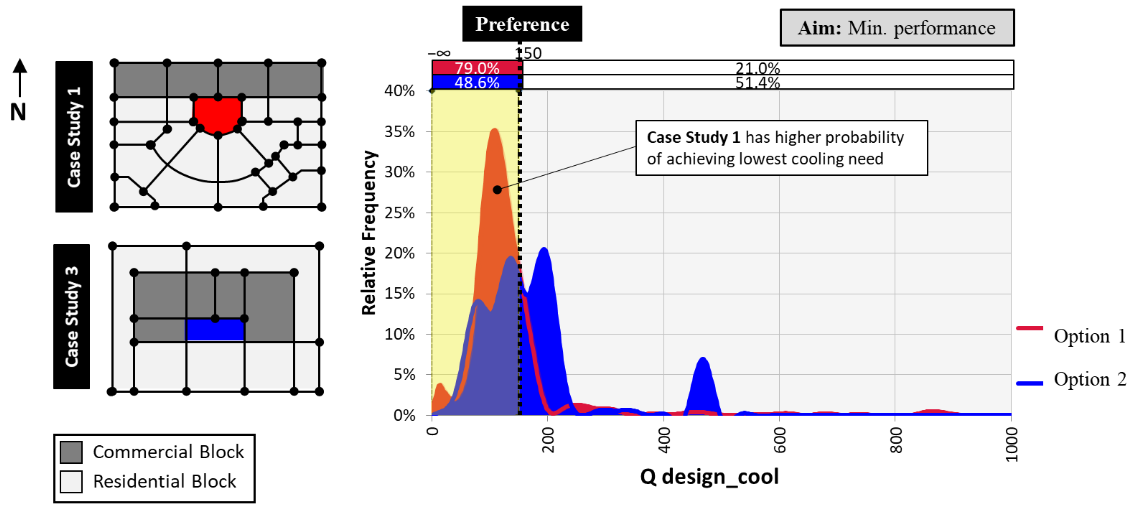



**Figure 4.49: Performance measure-5 for different urban fabric options**

## 4.5 Conclusion

This chapter populates the intended implementation of a framework for applying performance-based decisions in early design with a set of concrete (non-exhaustive) performance measures. The proposed approach is underpinned by the following:

- Segments the urban design concept generation phase into a step-by-step process, combining both user-defined and automated components, which do not restrict the designer's creativity while at the same time allowing designer to see the full potential of generated design alternatives.

- Proposes multiple reduced order urban performance measures to respond to the need for performance evaluation at early design phase. This allows informative exploration of design option space, leading to robust decisions (Haymaker, et al., 2018).

- Considers undecided design parameter uncertainty that are an unavoidable part of each option the design option space, hence replacing the sole reliance on deterministic outcome prediction.

It is shown how the proposed methodology can be applied and implemented for each introduced performance measure separately thus establishing the viability of the approach. However, in real case scenarios, multiple performance measures are evaluated alongside concurrently as urban design is a multi-objective design problem. In the next chapter the proposed framework is applied on a real urban design problem with multiple performance objectives. Its main purpose will be to investigate the feasibility of application in the urban design process. It will also be used to showcase the implementations in a Rhino-grasshopper platform.

# CHAPTER 5. FEASIBILITY ANALYSIS OF PROPOSED APPROACH

## 5.1 Introduction

In this chapter two real urban design settings are chosen and used as case studies to test the proposed method. Both design processes are followed, and the proposed approach is applied to evaluate performance measures as design progresses. Designer chosen target values for performance measures are defined at the first stage and their percentiles of the response space are computed for each measure and for each design variant. The aim of this chapter is to track the trajectory of two traditional design processes and incorporate the performance-based decision-making approach to compare generated urban design options based on their potential in achieving stated performance objectives. The close inspection of how the proposed rational decision making applies to two traditional design cases is used to make statements about feasibility of the approach in general.

## 5.2 Case Study 1: Residential Block, Oman

The first case study is a residential block located in the interior region of Oman (Figure 5.1), the aim of designing this block is to have a private residential community with necessary amenities provided within the boundary of the site. The boundary of the site is defined by mountain from one side and rain-water run-off from the other side. There is virtually no surrounding context to the site as it is a relatively new community. The design goal of this residential block is to have a private community with low connectivity with the outer network, an outdoor space with high visual properties and thermal comfort, along with units with low energy consumption and high percentage of naturally daylight hours.


**Figure 5.1: Case study 1 site location and boundary**

### *5.2.1 Design Process*

In the actual, traditional design process multiple options were generated to fulfil the design objective of creating a liveable community. Based on the designer's intuition and experience, few of these design options were chosen to be detailed by plot subdivision as per land use. Many of the design options were in fact disregarded early in the design process, assuming that they would not be able to fulfil the design objective. The selection of feasible design options was more often than not based on heuristics and sometimes pragmatism, simply because the burden of carrying all the options to the design detail phase is not feasible.

Land boundary and site entry points are the only decided parameters in this case study, the decision point is street network, hence proceeding towards this decision point the associated design parameters are not yet decided and hence in our approach regarded as uncertain (Figure 5.2).

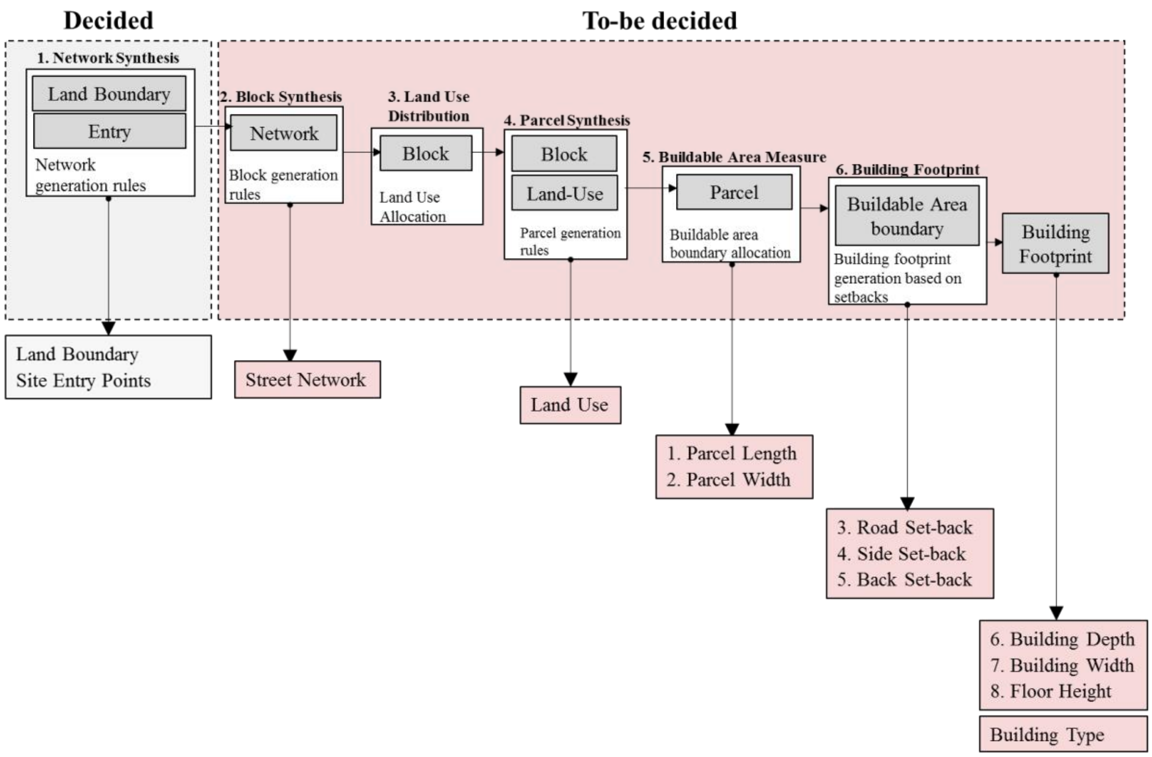



**Figure 5.2: Decided and undecided design parameters in case study 1**

### *5.2.2 Application of the proposed performance-based decision-making approach*

In this section, the performances of different design options will be tracked and compared with each other in terms of potential of achieving performance targets while considering design parameter uncertainty of undecided parameters.

Uncertainty in design parameters, such as: street network, land use and building type can only be represented as a set of options, represented as discrete uncertainties, whereas parameters such as: parcel dimensions, building setbacks and building geometry can be represented as continuous parameter distributions (Table 5.1).

**Table 5.1: Undecided parameter input, Case study 1**

| Parameter | Distribution, Range | | |
|---|---|---|---|
| **Parcel:** | **Residential (Freestanding)** | **Residential (row house)** | **Commercial** |
| Plot Length (m) | Pert (15,18,30) | Uniform (12,15) | Pert (20,30,40) |
| Plot Width (m) | Pert (12,15,20) | Uniform (10,12) | Pert (15,20,30) |
| **Buildable Area:** | | | |
| Road Set-back (m) | 5 | 3 | 8 |
| Side Set-back (m) | 3 | 0 | 5 |
| Back Set-back (m) | 3 | 3 | 5 |
| **Buildable Area:** | | | |
| Building Depth (m) | Uniform (12,25) | Uniform (10,12) | Uniform (15,25) |
| Building Width (m) | Uniform (10,15) | Uniform (10,12) | Uniform (12,20) |
| Floor Height (m) | Pert (2.5,3.5,4.5) | Pert (2.5,3.5,4.5) | Pert (2.5,3.5,4.5) |

At the decision point of street network design, two types of networks were proposed. In the first option, the street network is distributed to be highly connected to the external road network, whereas in the second option a more enclosed network was proposed. By comparing performance measure-1 of both the options while considering uncertainty in land use, it is noted that option 1 has high percentage of by-product block (explained in section 4.4.1) as compared to option 2. Since the objective of design is to create a private residential area, the percentage of by-product block needs to be reduced to minimize unnecessary traffic flow. A target of 25% is set for this measure, and it is noted that option 2 has 40% probability of achieving a by-product percentage less than 25% as compared to option 1 that only has 10% probability of achieving the same percentage. This makes option 2, an enclosed street network the clearly preferred option (Figure 5.3).

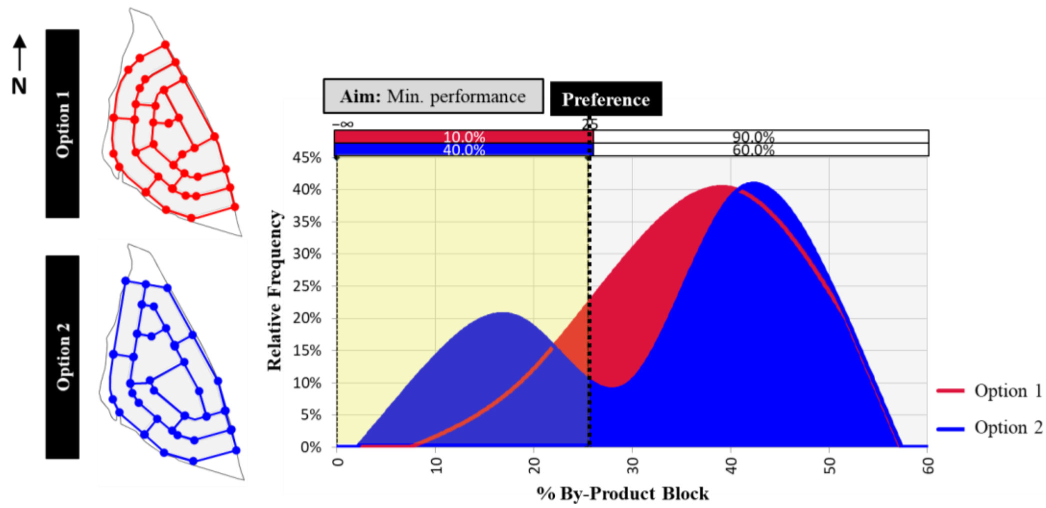



**Figure 5.3: Performance measure -1 for two options**

Designers further subdivided options 1 and 2 into several design alternatives with difference in land use and street network subdivision (Figure 5.4). Not all of these alternatives were carried on to the detail design stage, but they are used here for performance comparison in the proposed approach.

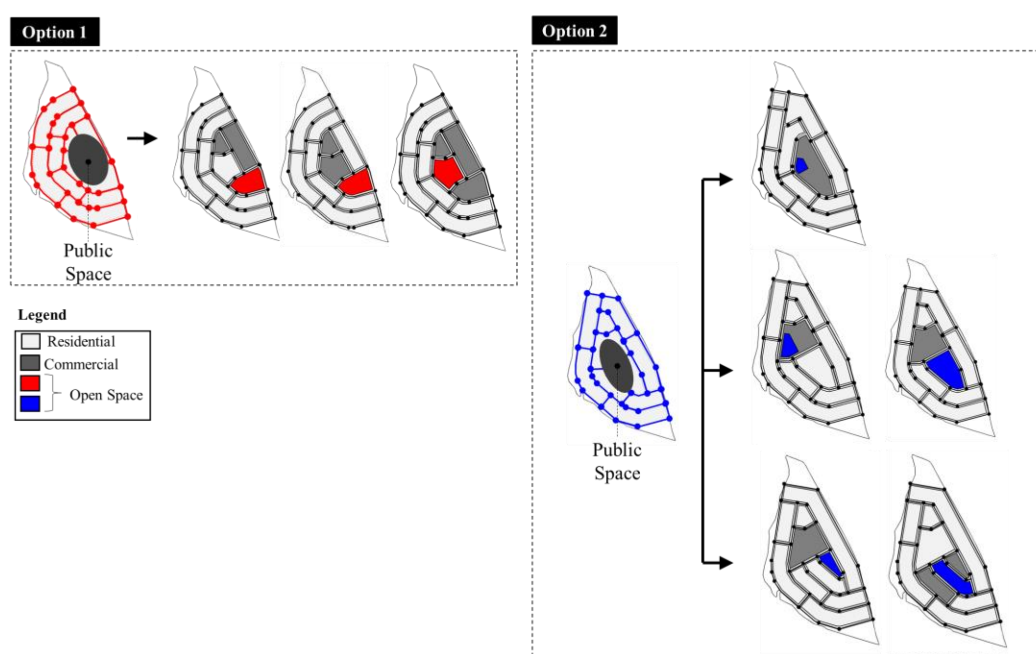



**Figure 5.4: Classification of options generated in the design process**

The outcomes for performance measure-2 are compared for four open spaces of the proposed design alternatives. With placing open space in an urban block, the aim is to maximize its visibility and visual complexity. It is noted from comparison that options 1 and 3 have greater potential in achieving relatively high total visibility as compared to options 2 and 4. Whereas option 4 has significantly greater potential in achieving high value in total visual complexity as compared to rest of the options. Making a choice in this case is not very clear, as there is trade-off between visibility and complexity.

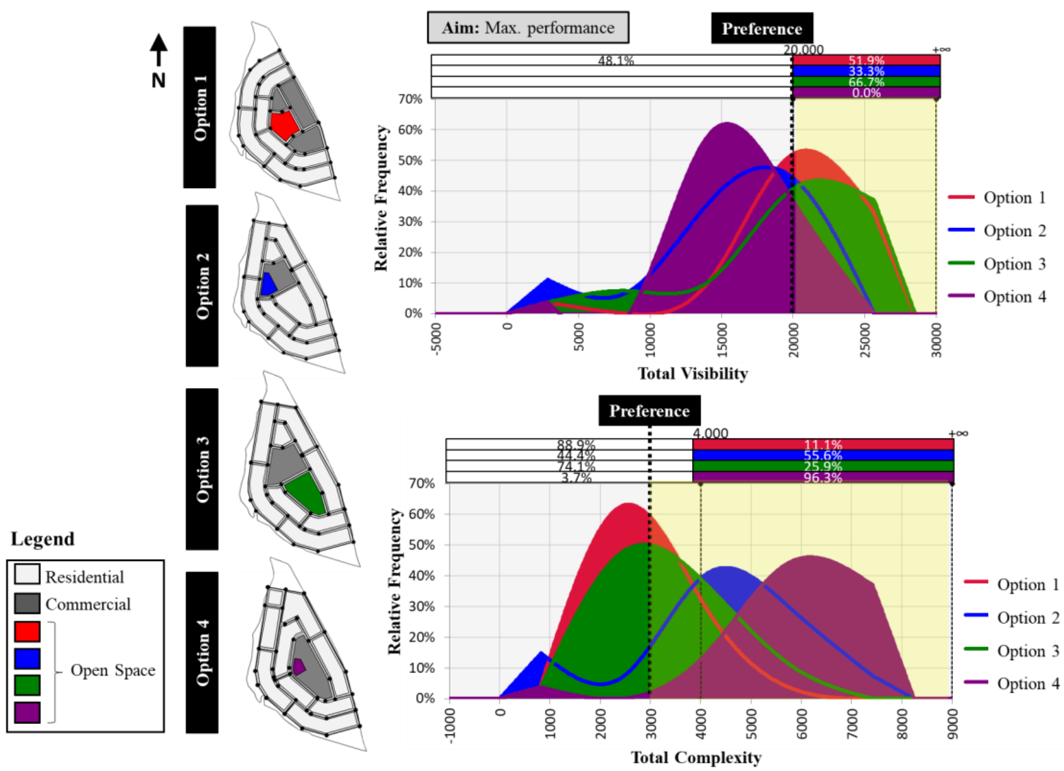



**Figure 5.5: Performance measure-2 for different open space and land use allocation options**

Performance measure-3 is compared for the four design alternatives of different open space placement (from the previous example). It is noted that although these options have significant differences in visual performance, their outdoor thermal comfort performance is relatively indifferent (Figure 5.6), reminding us of the general insight that comparing different design alternatives will not always lead to a clear preference in all performance measures.

Visual performance of open space is highly correlated to the geometry of the open space and uncertainties in building geometry design parameters don't have a considerable impact on the visual performance as seen in the following comparison (Figure 5.7).

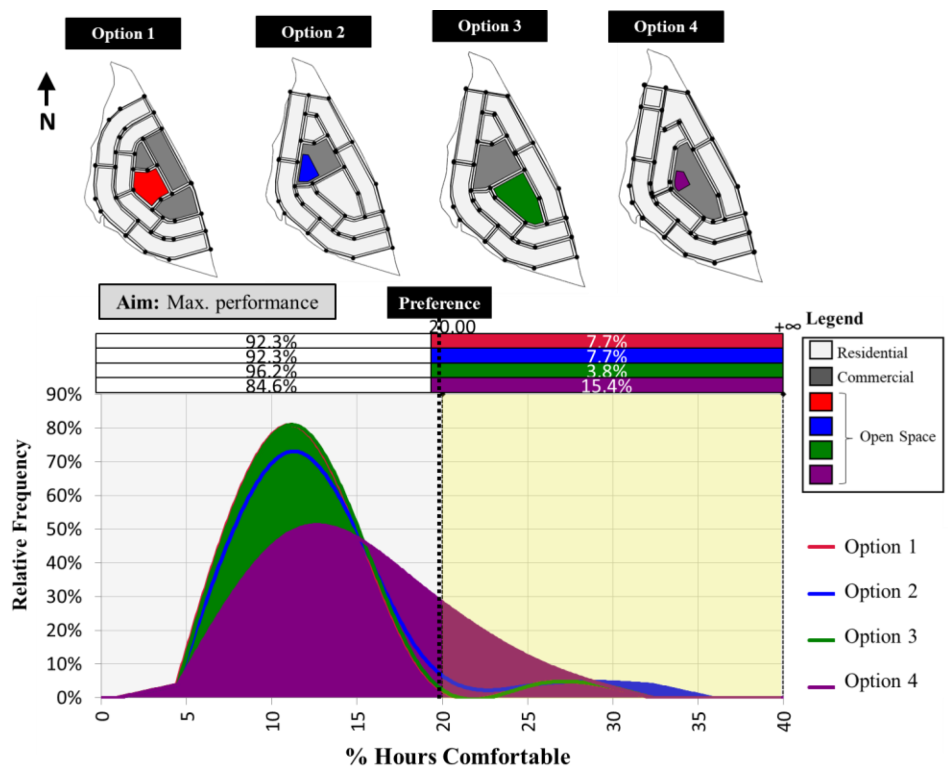



**Figure 5.6: Performance measure -3 for different open space and land use allocation options**

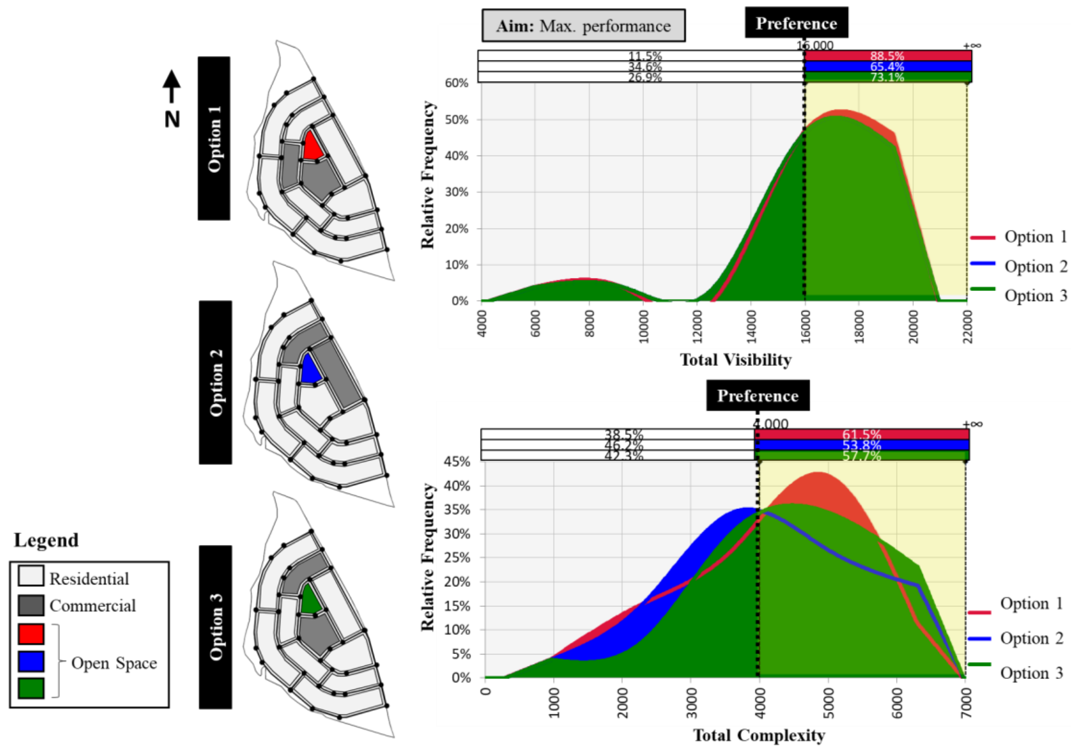



**Figure 5.7: Performance measure-2 for different open space and land use allocation options**

Although comparing similar open space geometry with different surrounding land use is indifferent for performance measure-2, it has high impact on performance measure-3. Outdoor thermal comfort is extremely sensitive to orientation and location of surrounding land use. This is evident in comparing the same design options for performance measure-3 (Figure 5.8), in which option 1 has the greater potential in achieving higher percentage of outdoor thermal comfort as compared to options 2 and 3.

In a different comparison, another open space placement is compared with different surrounding land use (Figure 5.9). It is evident from this comparison that option 2 has significantly higher potential in achieving the target outdoor thermal comfort performance as compared to options 1 and 3.

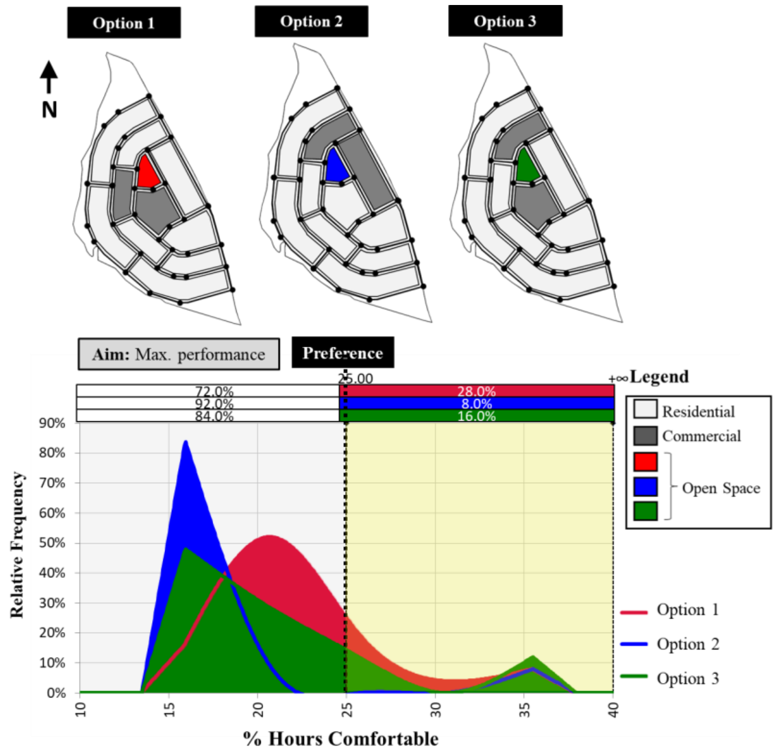



**Figure 5.8: Performance measure-3 for different land use allocation options**

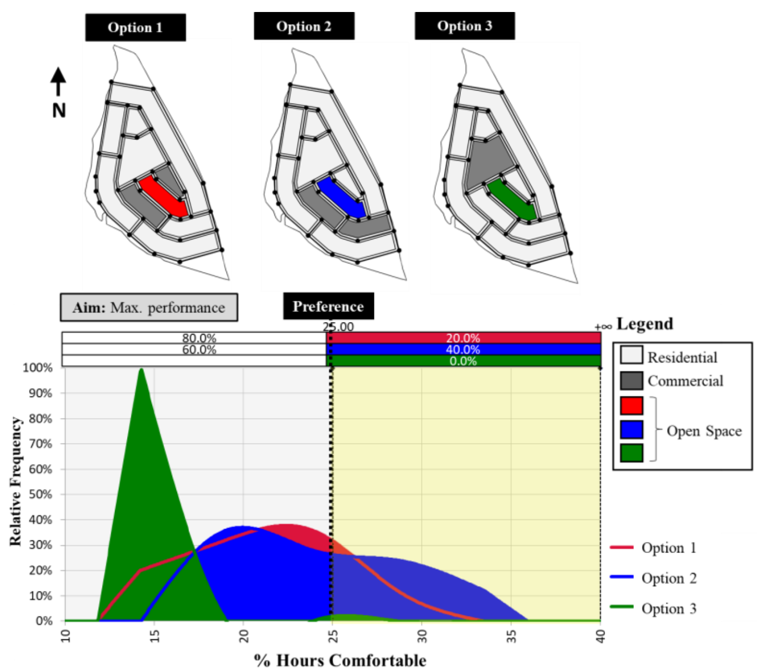



**Figure 5.9: Performance measure-3 for different land use allocation options**

Based on multiple design option comparisons, three designs were further compared for performance measures 4 and 5 and another design parameter was added, which is building type, as performance measures 4 and 5 are impacted significantly by this parameter.

By comparing performance measure-4 of the three chosen options, it is evident that option 3 has a relatively higher potential of achieving target of 50% of buildings with interior illuminance greater than 300 lux as compared to rest of the options (Figure 5.10).

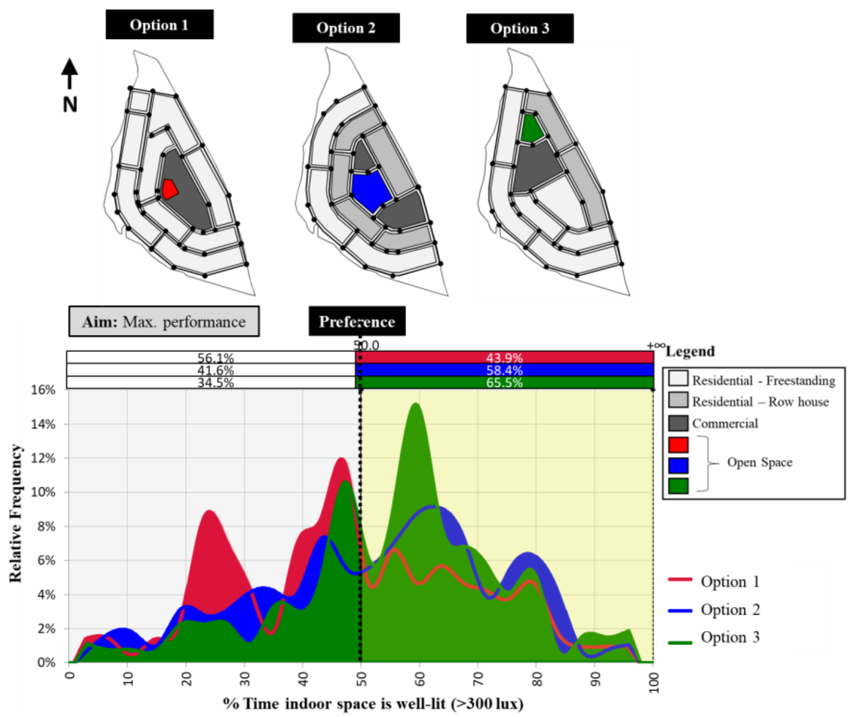



**Figure 5.10: Performance measure-4 for different open space and land use allocation options**

The same design options (Figure 5.10) are then compared for performance measure-6, which is urban energy consumption. It is evident from the comparison that option 1 has significantly higher potential in achieving cooling need per building of less than 150 kWh/m$^2$ as compared to options 2 and 3 (Figure 5.11). Although option 1 had comparatively low potential in achieving the target for performance measure-4, it proves to be a clear preference for performance measure-5.

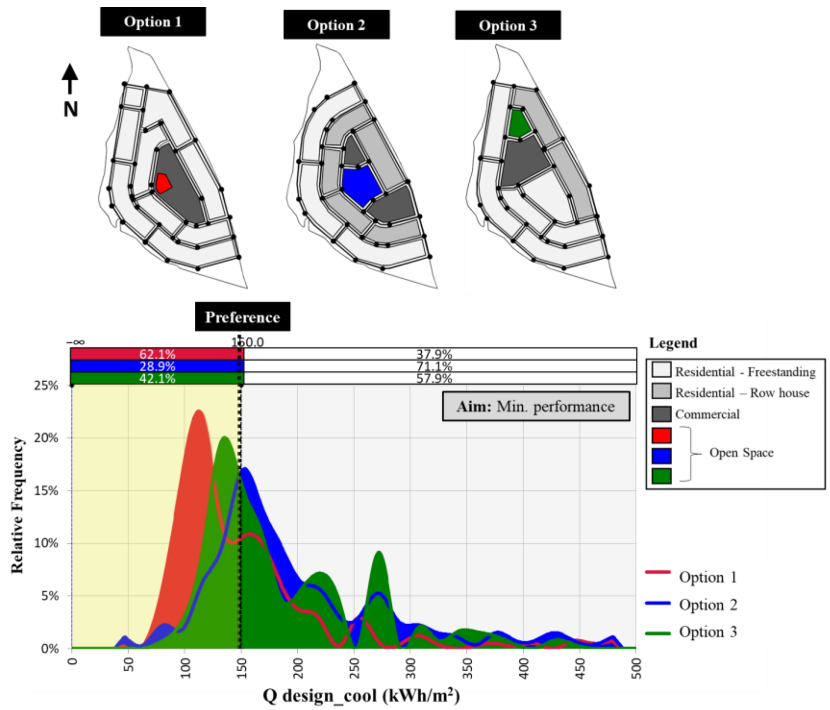



**Figure 5.11: Performance measure-5 for different open space and land use allocation options**

Option 1 from the previous example is further explored by changing building type distribution in the urban fabric. It is noted that by changing the building type distribution in the urban fabric both performance measures 4 and 5 are significantly impacted. Based on performance measure-4 comparison, it is noted that options 2 and 3 have higher potential in achieving the target of interior building daylight as compared to option 1 (Figure 5.12). However, when comparing performance measure-5 it is noted that option 1 has significantly higher potential in achieving building energy target as compared to options 2 and 3 (Figure 5.13). In such cases, the decision maker needs to decide which performance measures should receive priority over others.

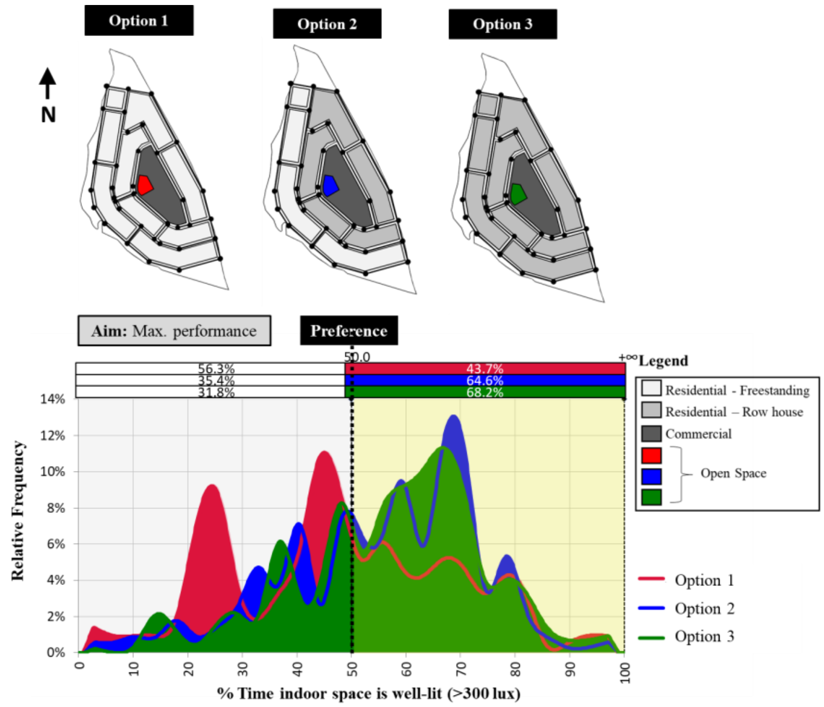



**Figure 5.12: Performance measure -4 for different land use allocation options**

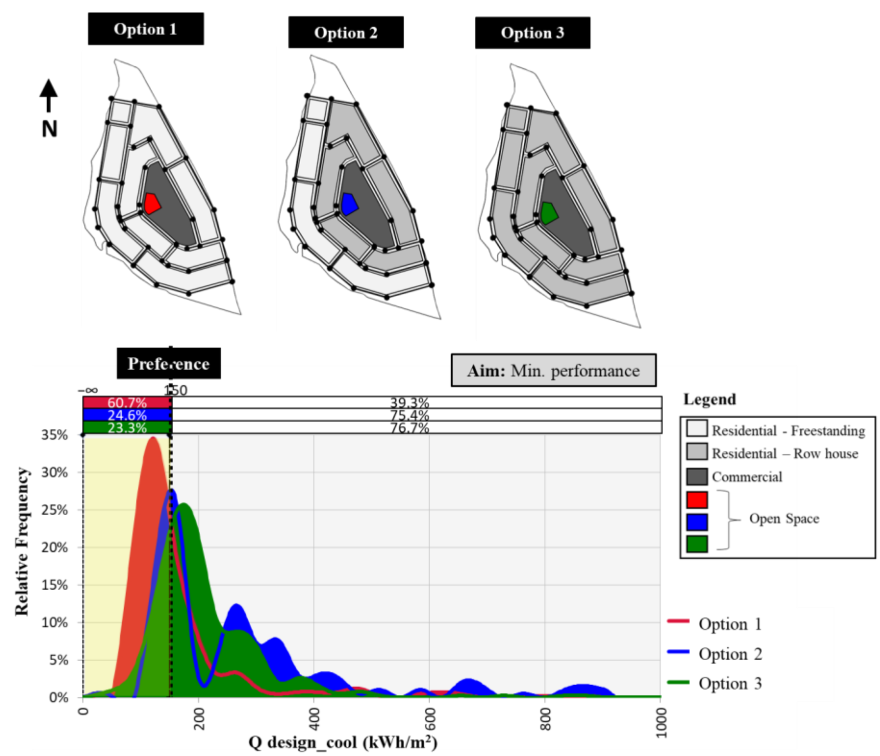



**Figure 5.13: Performance measure -5 for different land use allocation options**

### 5.2.3 *Discussion*

In the actual design process, option 1 (Figure 5.14) was chosen as the final design proposal to be implemented based on designer's experience and intuition, i.e. following traditional methods. To inspect this further, a rejected design option from the early design stage is compared with the chosen design for selected performance measures. It is noted from comparing all five proposed performance measures against their established targets that the rejected alternative (option 2) and chosen design option (option 1) are in fact competitive options as indicated by the results shown in Figure 5.14.

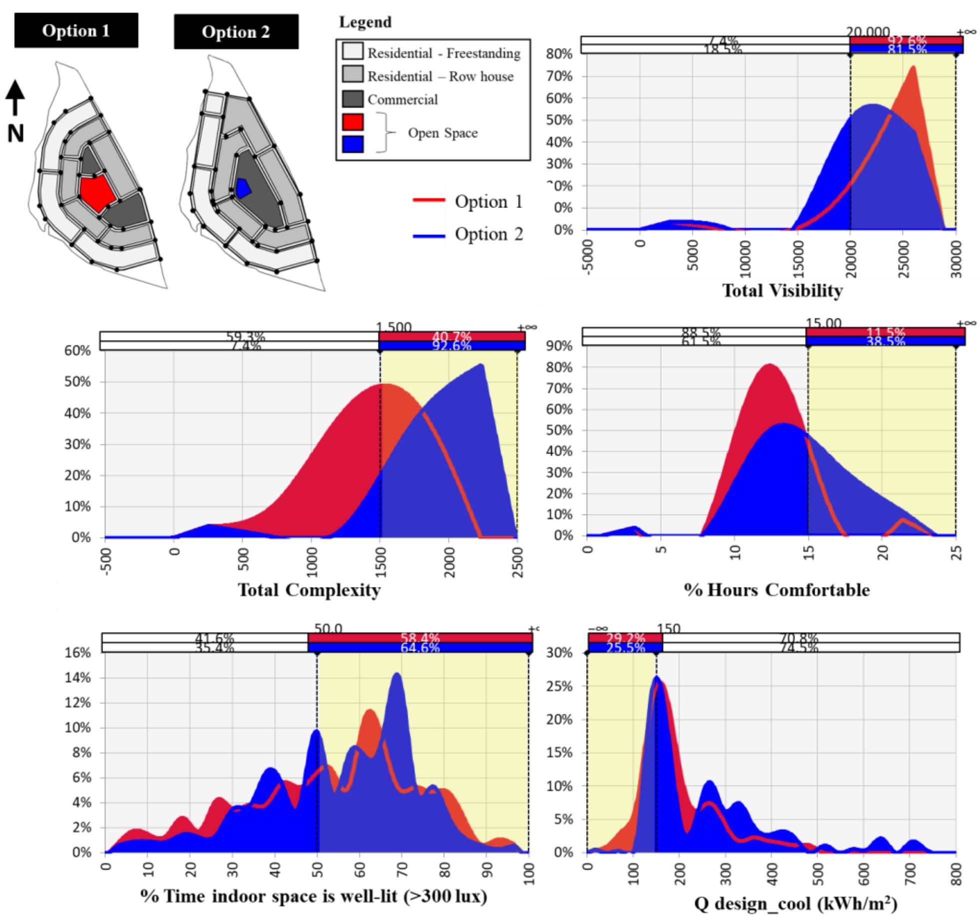



**Figure 5.14: Comparison between performance measures of a chosen option (Option 1) and an option rejected in traditional early design stage (Option 2)**

This indicates that indeed, as we argued before, there may be a high but unnoticed potential of design alternatives that are rejected at the early design stage without enough exploration. Relying solely on designer's experience and intuition is then not sufficient as there are many aspects of performance that cannot be evaluated based only visual evaluation of the urban design, it needs further computation and inspection of all possibilities before making a confident decision. It may also indicate that a first order assessment of what leads to the best outcomes can be misleading if there are too many undecided design parameters that influence the outcome. Intuition about the expected outcomes in the light if undecided variables is lacking and hence a formal assessment based on propagation is clearly the better basis for the decision to reject a design variant.

## 5.3 Case Study 2: Duqm Area Tourism Zone, Oman

The second case study is an isolated site located in Duqum area, which is at the coast of Southern Oman. The aim of developing this site in the Duqum area is to establish a tourist attraction and accommodation at the sea front. This frontier town will the first residential area added to the tourism zone (Figure 5.15).

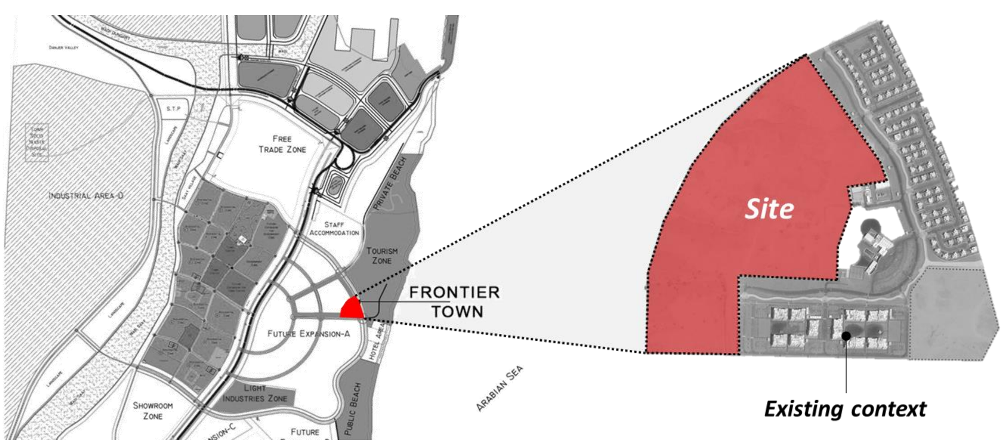



**Figure 5.15: Duqum area site location and context**

An important aim of developing this area is to have a mixed-use residential community integrated with new roads and paths extending from the existing network and where the open spaces form an extensive network of paths that connect the clusters to the exiting development and the surrounding. The development will provide residents with facilities required to form an integrated community with appropriate use of leisure and recreational facilities that will also provide direct connections to larger commercial areas and amenities within the Duqum Central Area. The design goal of this tourism block is to have a community with high connectivity with outer network, outdoor space with high visual properties and thermal comfort, along with units with low energy consumption and high percentage of natural daylight hours.

### *5.3.1 Design Process*

Three spatial options were developed in response to the site's development constraints. Each option tries to explore different ways in which the objectives may be spatially implemented (Figure 5.16). The starting point for the options was an exploration of how residential densities could be spatially arranged on the site and the difference in overall dwelling yield achieved under different residential product mixes.

(a) (b) (c)

**Figure 5.16: Three proposed design options for the site**

The options also propose different ways in which non-residential uses as placed in proximity to the external boundary, are placed in proximity to direct public access. Overall there was no single option seen as most successful. Instead, there were strengths and preferences identified across all three options.

In contrast to case study 1, this case study is further along in the decision process, as the street network and land use have been fully identified in the three design options. The remaining undecided design parameters are parcel dimensions and building geometry (Figure 5.17).

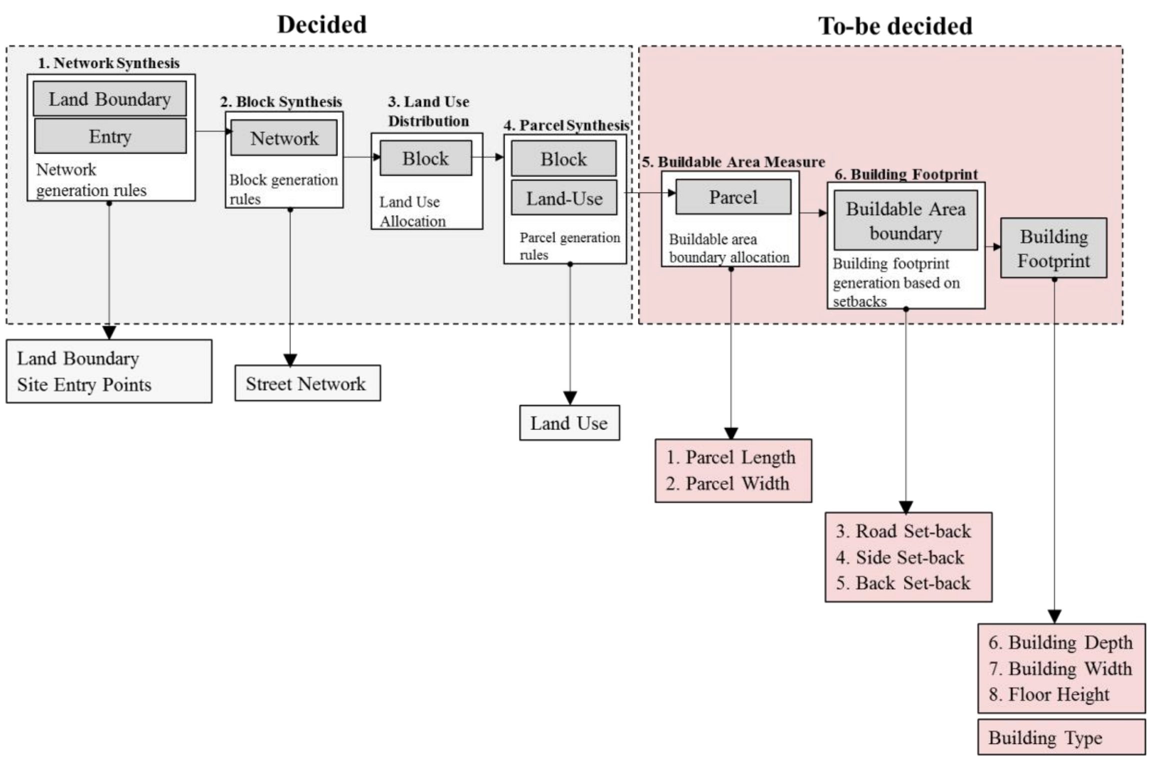



**Figure 5.17: Decided and undecided design parameters in case study 2**

Considering these undecided parameters, the task is to identify the design option from the three proposed alternatives that has the most potential in achieving the set performance targets. Unlike case study 1, the treatment will be limited to the proposed three options as the design phase is further advanced in case study 2, which makes the rational choice of the preferred alternative among three discrete options an appropriate application focus of the case study.

### *5.3.2 Application of proposed performance-based decision-making approach*

In this section, the performances of three proposed design options are compared with each other in terms of potential of achieving performance targets while considering design parameter uncertainty of undecided parameters.

Since the decision-making point is further along in the design process, the remaining uncertainty in design parameters are parcel dimension and building geometry. The design parameter uncertainty ranges and distributions are defined in Table 5.2.

**Table 5.2: Undecided parameter input, Case study 2**

| Parameter | Distribution, Range | | | |
|---|---|---|---|---|
| **Parcel:** | **Residential (Type-1)** | **Residential (Type-2)** | **Residential (Type-3)** | **Commercial** |
| Plot Length (m) | Pert (15,18,30) | Uniform (12,15) | Uniform (15,30) | Pert (20,30,40) |
| Plot Width (m) | Pert (12,15,20) | Uniform (10,12) | Uniform (12,20) | Pert (15,20,30) |
| | **Buildable Area:** | | | |
| Road Set-back (m)<br>Side Set-back (m)<br>Back Set-back (m) | 5<br>3<br>3 | 3<br>0<br>3 | 5<br>0<br>0 | 8<br>5<br>5 |
| | **Buildable Area:** | | | |
| Building Depth (m)<br>Building Width (m)<br>Floor Height (m) | Uniform (12,25)<br>Uniform (10,15)<br>Pert (2.5,3.5,4.5) | Uniform (10,12)<br>Uniform (10,12)<br>Pert (2.5,3.5,4.5) | Uniform (12,25)<br>Uniform (12, 20)<br>Pert (2.5,3.5,4.5) | Uniform (15,25)<br>Uniform (12,20)<br>Pert (2.5,3.5,4.5) |

The proposed performance-based decision making is applied using the five performance measures developed in section 4.4 for comparison. In doing so, design uncertainty is only applied to four of these measures as design parameters needed to compute performance measure-1 are fully decided by preceding design steps for all three design options, hence resulting a deterministic result for this performance measure.

It is noted by comparing three design options, that design option 1 has the highest percentage of by-product blocks and since the aim of the design is to have a well-connected, integrated and active community, the aim is to have a high percentage of by-product block. Option 1 is the only option that can provide a percentage of 50%, indicating that almost half of the blocks are highly integrated with the street network (Figure 5.18).

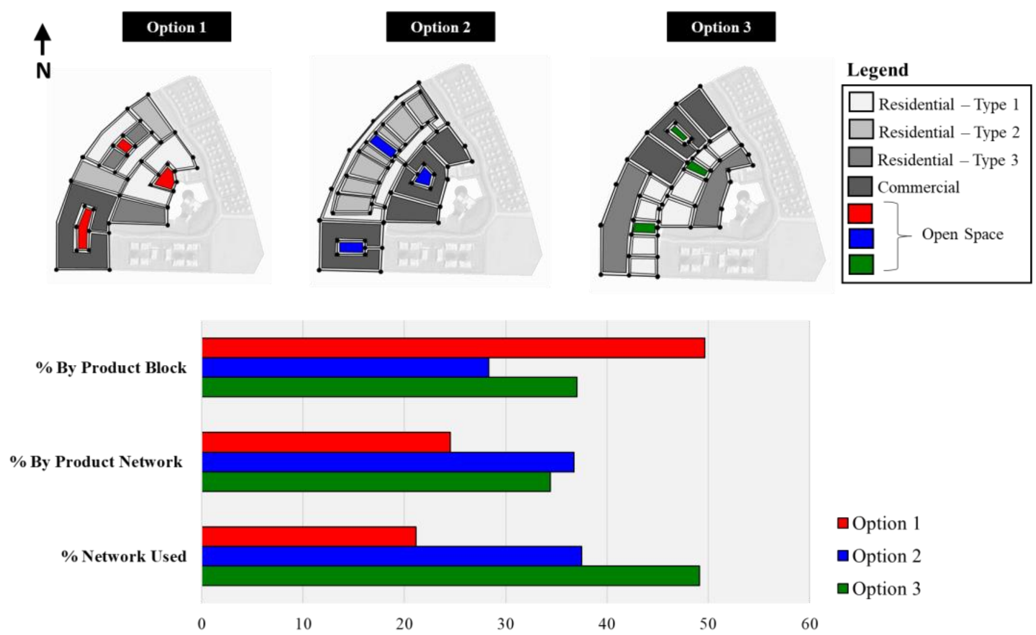



**Figure 5.18: Performance measure-1 for three options**

Open spaces in the three design options are proposed as integrated within building clusters. By comparing the outcomes of performance measure-2 for the three design options, it can be seen that although option 1 has the highest probability of achieving high visual performance as compared to the other two options, option 3 has more potential in achieving visual complexity in open spaces as compared to the rest of the options. The trade-off in this case is thus between visual performance and visual complexity (Figure 5.19). Performance measure-3 is then compared across the three options and it is noted that option 3 has the highest potential of achieving greater percentage of comfortable hours in the open spaces as compared to the other two options (Figure 5.20).

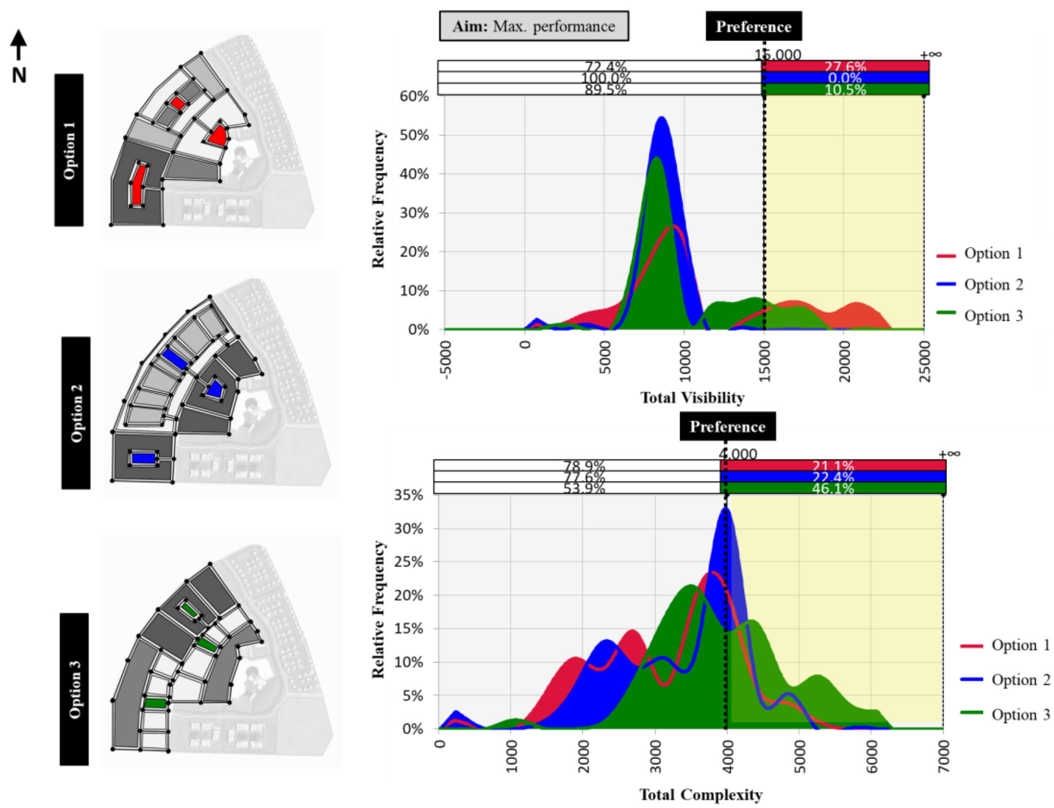



**Figure 5.19: Performance measure-2 for three design options**

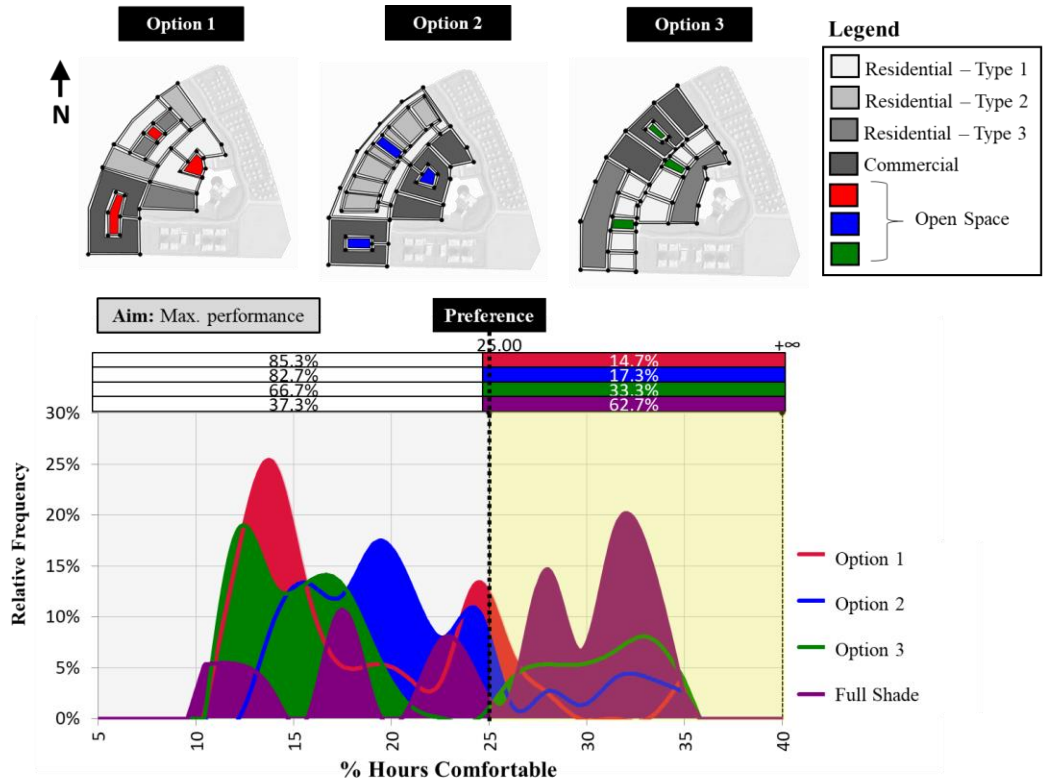



**Figure 5.20: Performance measure -3 for three design options**

Performance measure-4 is also compared for the three options and it is noted that option 2 has a higher potential of achieving cooling energy performance per building of less than 150 kWh/m$^2$, however the difference in performance with the other two design options is not significant (Figure 5.21).

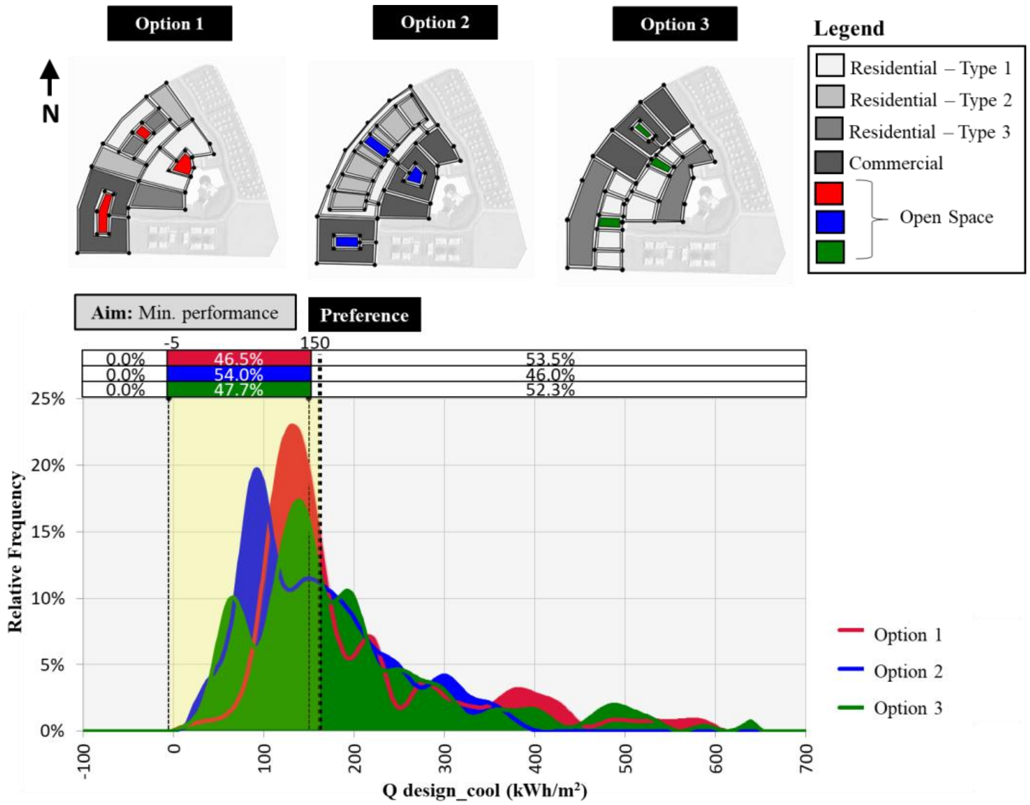



**Figure 5.21: Performance measure-4 for three design options**

Finally, the outcomes of performance measure-5 are compared for the three options and it is noted that both options 1 and 2 have relatively similar potential of achieving interior illuminance of more than 300 lux half of the occupied time (Figure 5.22).

After comparing all three proposed design options for different performance measures, it is noted that option 1 and 2 have competitive outcomes. Indicating that both have similar potential of achieving the performance targets based on the defined design uncertainties.

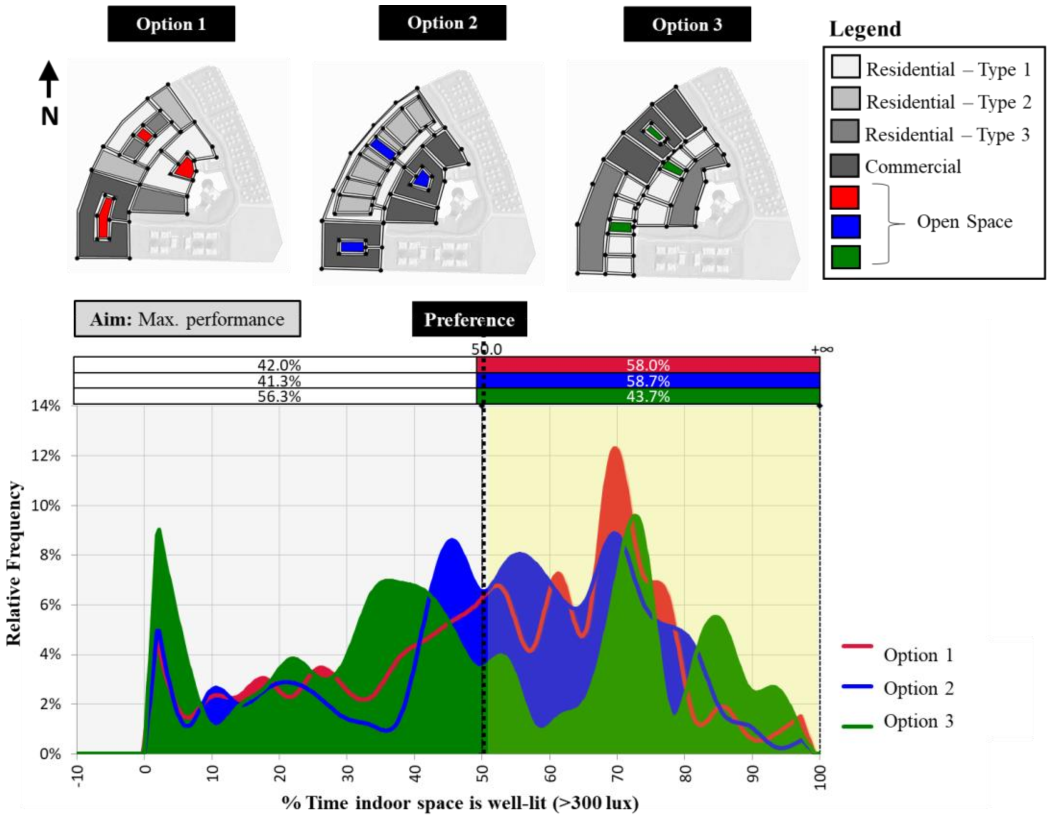



**Figure 5.22: Performance measure-5 for three design options**

### *5.3.3 Discussion*

In the actual case, following a traditional design process, option 2 was chosen as the final urban scheme to be implemented (Figure 5.23). Although the method developed in this thesis did provide good guidance in choosing between three design alternatives, for instance it shows that options 1 and 2 outperform option 3, the full benefit of the proposed approach is somewhat limited at this late decision-making point. Since the three design options were largely developed at the decision-making point, the potential impact of future design decisions is rather reduced and the outcomes of the analysis less decisive.

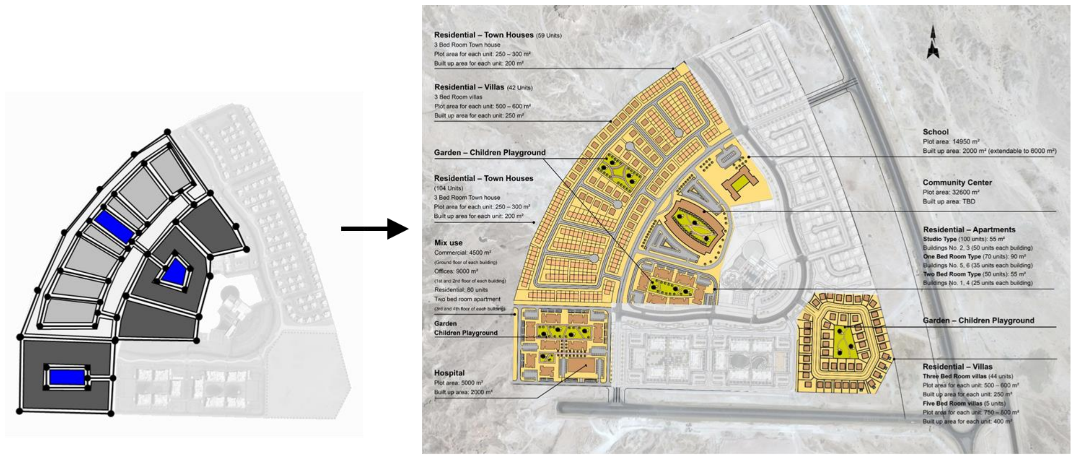



**Figure 5.23: Chosen design option in design case 2 in traditional process**

## 5.4 Conclusion

In this chapter two distinctly different case studies were chosen in terms of design objective and decision-making stage in the design process. In the first case study, the decision point was early in the process, which invites to evaluate a wide range of design possibilities. It was also noted that many of competing design options were discarded early in the design stage that might have proven to be competitive design options in terms of presented performance measures. In contrast, case study 2 was further along in the design process, hence the decision making was limited to three fully developed design options with limited design uncertainties. In both case studies the feasibility of supporting the selection between alternatives is proven if an adequate computational framework is available to the designer. The resulting rich information should lead to better decisions, be it in relation to an early decision not to pursue a certain variant, or in the prioritization of the most preferred variant.

The proposed approach guides the decision making in both case studies by explicitly quantifying design uncertainty and considering it in calculating the performance measures, which expresses the possibility of a design option to achieve a performance target. The first case study shows that this can be an important consideration beyond the simple first order assessment in prioritizing or discarding a certain variant. Allowing the designer to fully understand the potential of a design option is important, and current early stage assessment arguably falls short of this.

The feasibility assessment in this chapter underlines a weakness of the proposed approach which is the reliance on the designers' ability to express design uncertainties. This is unavoidable at this early stage of the development, i.e. until a general and authoritative source has been developed. This will be further discussed in future directions (section 8.2).

# CHAPTER 6. COMPARISON OF THE PROPOSED METHOD WITH RULES OF THUMB IN EARLY DESIGN

## 6.1 Introduction

Due to the lack of a proper method for informed and exhaustive exploration of the urban design space at the early stage of design, a performance-based decision-making approach is developed in this thesis that provides this capability. Currently, early design stage decision making relies mostly on designer experience and rules of thumb, which are considered sufficient at the early stage even if one accepts that they may be affected by unconscious biases. This thesis argues that relying on generalized rules of thumb when making early urban design decisions expecting that following these rules of thumb leads to better 'performing' urban fabric is questionable in the light of design uncertainties. In the broader perspective, it is appropriate to be skeptical towards the use of rules of thumb unless they have been validated.

Hazelrigg (Hazelrigg, 2012) describes model validity in a design decision context, not in terms of an accurate estimation of an unrealized reality, but in terms of an accurate decision. As Hazelrigg describes:

*"A model is valid if, when used in a specific decision making situation with a given set of available alternatives and the decision maker's beliefs and preferences, the decision maker is certain that his preferred choice is the choice that indeed yields the outcome that is most preferred from among the outcomes that could have been obtained from the set of available alternatives."*

Chapter 5 of this dissertation explains that implementation of the proposed performance-based decision making is based on the quantification of the confidence level of achieving a given performance objective. This is justified by the definition of model validity by Hazelrigg, as the method will indeed enable the designer to select preferred outcome based on rationality.

The next step is to compare the advantage of the proposed method compared to current early design decision making approaches. In this chapter, a general urban design rule of thumb is chosen and its effectiveness tested using a performance-based approach. This evaluates whether the given rule of thumb when used in making an early design decision leads to the "best" urban fabric option in terms of certain performance measures.

## 6.2 Rule of Thumb

As discussed earlier in this research, the spatial proximity of buildings can change the solar gain of buildings and alter the microclimate significantly, leading to changes in building energy consumption. As the solar radiation is the major source of heat gain of buildings, the mutual shadings of direct and diffuse solar irradiations by nearby buildings changes the heat balance of the building system and thus impacts the energy use (Olgyay, 1967; Olgyay, 1963). In addition to that, spatial distribution of buildings in the urban context impacts the geometry and composition of ground surface, leading to various microclimate patterns including temperature, wind flow and humidity at different locations (Golany, 1996).

The orientation and layout of streets has a significant effect on the microclimate around buildings and on the access to sun and wind for use in buildings. Because of this there have been many attempts to find general guidelines for urban fabric orientation based on climate characteristics. One of these attempts for finding generic solutions for a range of climates is introduced through a table of **“Street Orientation and Layout by Climatic Priority**” introduced by Brown and DeKay in their book Sun, Wind & Light (Brown & DeKay, 2001) as shown in Figure 6.1.

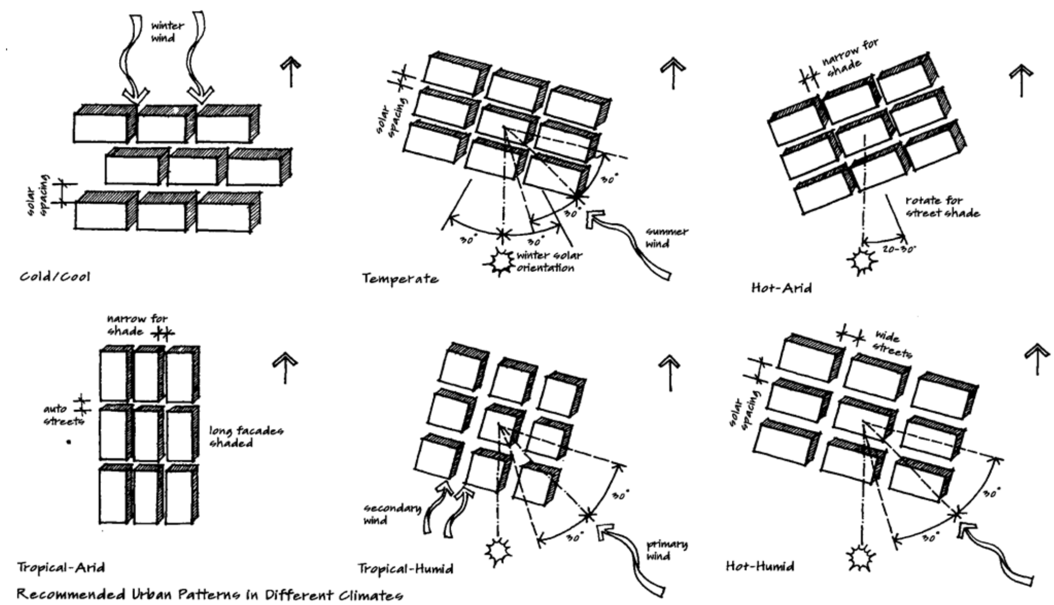



**Figure 6.1: Recommended urban patterns in different climate zones (Brown & DeKay, 2001)**

The rationale behind this orientation recommendation is that wider east-west streets give better winter solar access, while wider streets in the direction of prevailing wind flows promote better wind movement through the city. At high latitudes in the Northern Hemisphere, the sun is more South-dominant (North-dominant in Southern Hemisphere), while at temperate latitudes, more flexibility in orientation for solar heating is permissible without severe penalties in the amount of radiation collected. Narrow North-South streets can create shade from one building to the next (Brown & DeKay, 2001).

Although the justification of urban fabric orientation based on climatic characterization is reasonable, at the early stage of urban design there are multiple undecided parameters that also have significant impact on the energy use and outdoor thermal comfort. If these design parameter uncertainties are taken into consideration, the effect of the orientation of urban fabric on energy consumption and outdoor thermal comfort may be turn out to be small or even totally indifferent. This is explored in the next section.

### 6.3 Application of proposed method to orientation rule of thumb

In this section the effectiveness of the rule of thumb (Figure 6.1) discussed in section 6.2 is explored with the proposed performance-based decision making approach. Three different climate zones are chosen for the analysis: Atlanta (3A), Chicago (5A) and Miami (1A) as the rule of thumb recommendations are based on climate zones (Figure 6.2). The design options are four different orientations based on rules of thumb recommendations (Figure 6.1): option 1 is 0°, option 2 is -30°, option 3 is +30° and option 4 is 90°.

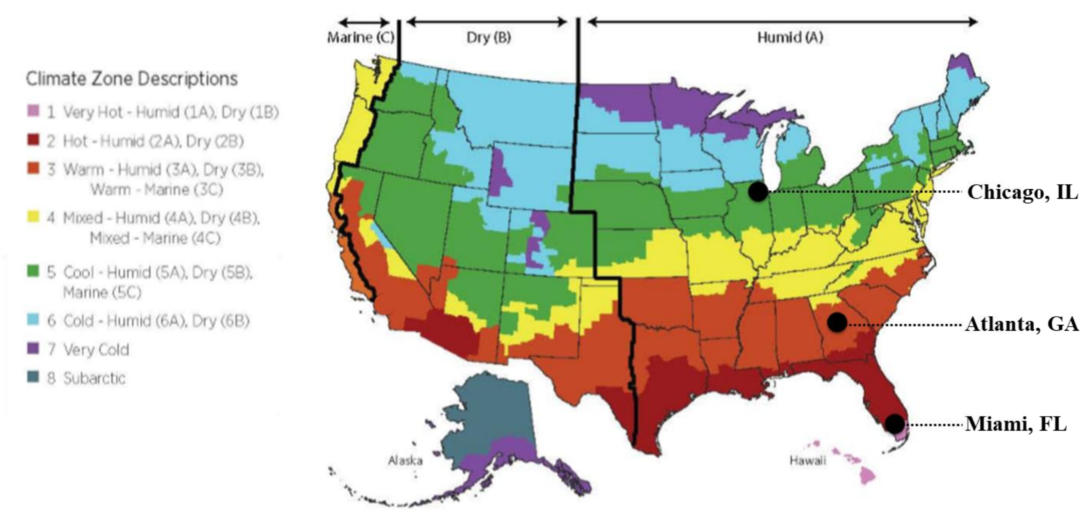



**Figure 6.2: Climate Zone map, based on ASHRAE 90.1, with chosen locations for analysis**

The chosen rule of thumb is applied when street network and building footprint have been defined and the undecided parameter is 'building envelope properties', which includes window-to-wall ratio and U-value of roof, wall and window. These properties are considered as design parameter uncertainties in the energy performance prediction, i.e. energy consumption calculation, and in the outdoor thermal comfort assessment.

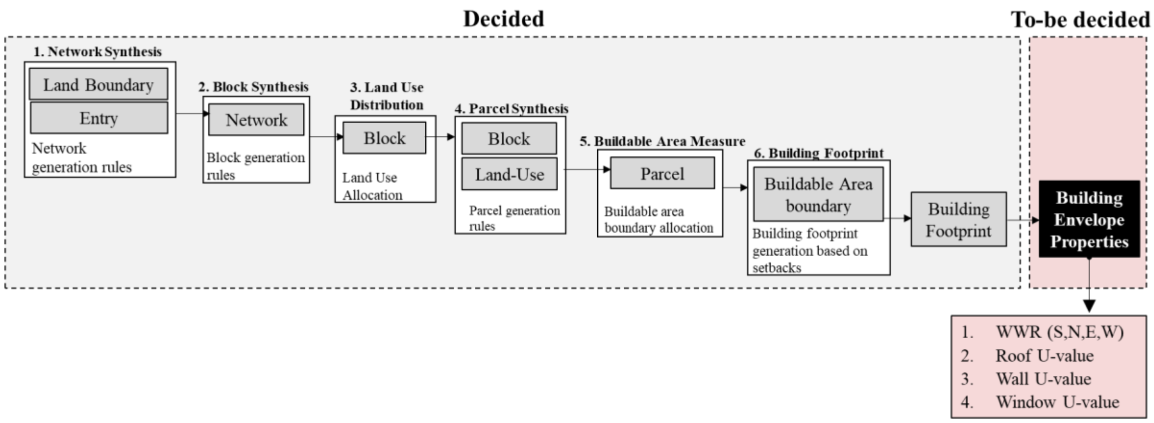



**Figure 6.3: Decided and undecided design parameters for the rule of thumb**

For the undecided building envelope design parameters, ASHRAE 2013 is used to define their value ranges (Table 6.1). Using Latin Hypercube Sampling, a total of 240 design options are generated and the two performance measures are computed for each option, i.e. energy consumption and outdoor thermal comfort.

**Table 6.1: Parameter ranges based on ASHRAE 2013**

| Parameter | Distribution |
|---|---|
| South WWR | Uniform (10%, 40%) |
| East WWR | Uniform (10%, 40%) |
| West WWR | Uniform (10%, 40%) |
| North WWR | Uniform (10%, 40%) |
| Roof U-value | Uniform (0.1, 0.27) |
| Wall U-value | Uniform (0.2, 3.29) |
| Window U-value | Uniform (0.7, 3.99) |

Four urban fabric orientation options (0º, -30º, +30º and 90º) are simulated for three different climate zones with parameter uncertainty applied to building envelope properties. For Atlanta, a warm-humid climate zone, it is noted that cooling need of options 1 and 3 have slightly higher potential in achieving cooling need less than 200 kWh/m$^2$ as compared to other options, whereas heating need for the four urban fabric orientations are almost indifferent, making it difficult to choose one option over the other. According to the rule of thumb recommendation, 30º orientation (option 3) is advised for low urban energy consumption, however based on the performance comparison both options 1 and 3 have similar performance potential (Figure 6.4).

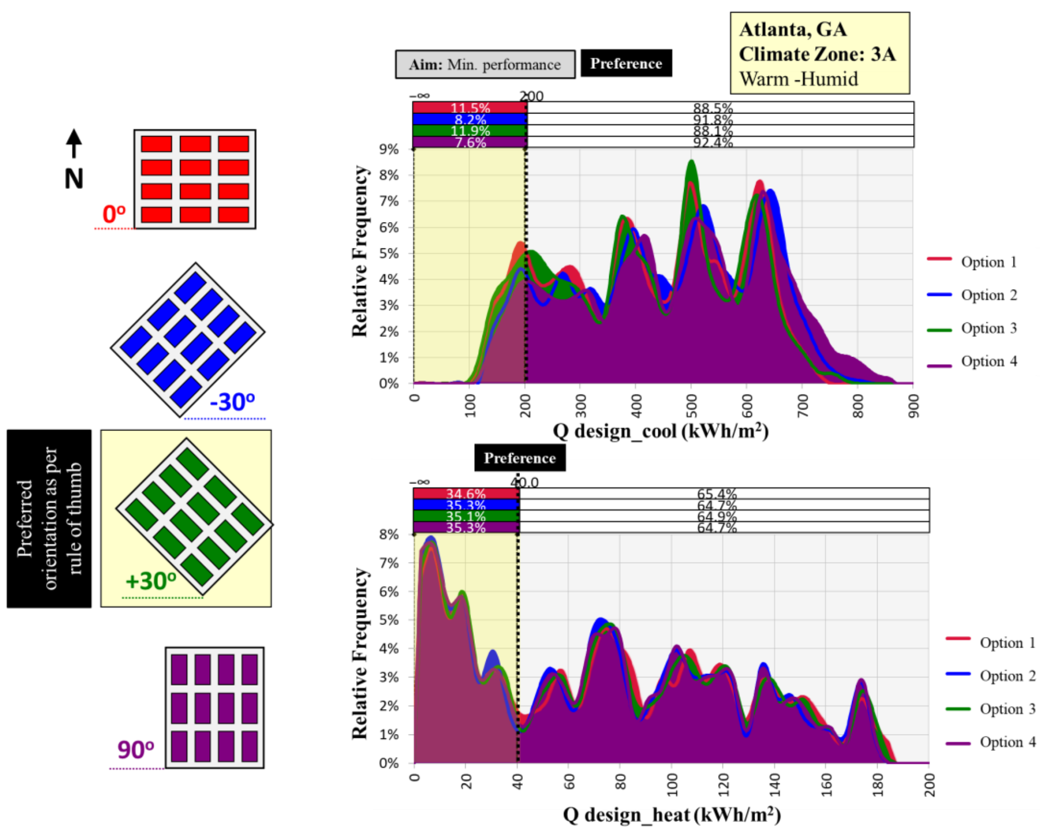



**Figure 6.4: Urban energy consumption (cooling and heating needs) for four different orientation options in Atlanta, GA**

Another location chosen for analysis is Chicago, which is considered a cool climate zone. Based on the urban cooling and heating needs, it is noted that option 3 has higher potential of attaining cooling need less than 100 kWh/m$^2$ and for heating need all options have more or less similar performance. Based on the rule of thumb recommendation, 0$^o$ orientation (option 1) is suggested for better energy performance. The recommended option is not in fact the best option, which contradicts the confidence in the option suggested by the rule of thumb (Figure 6.5).

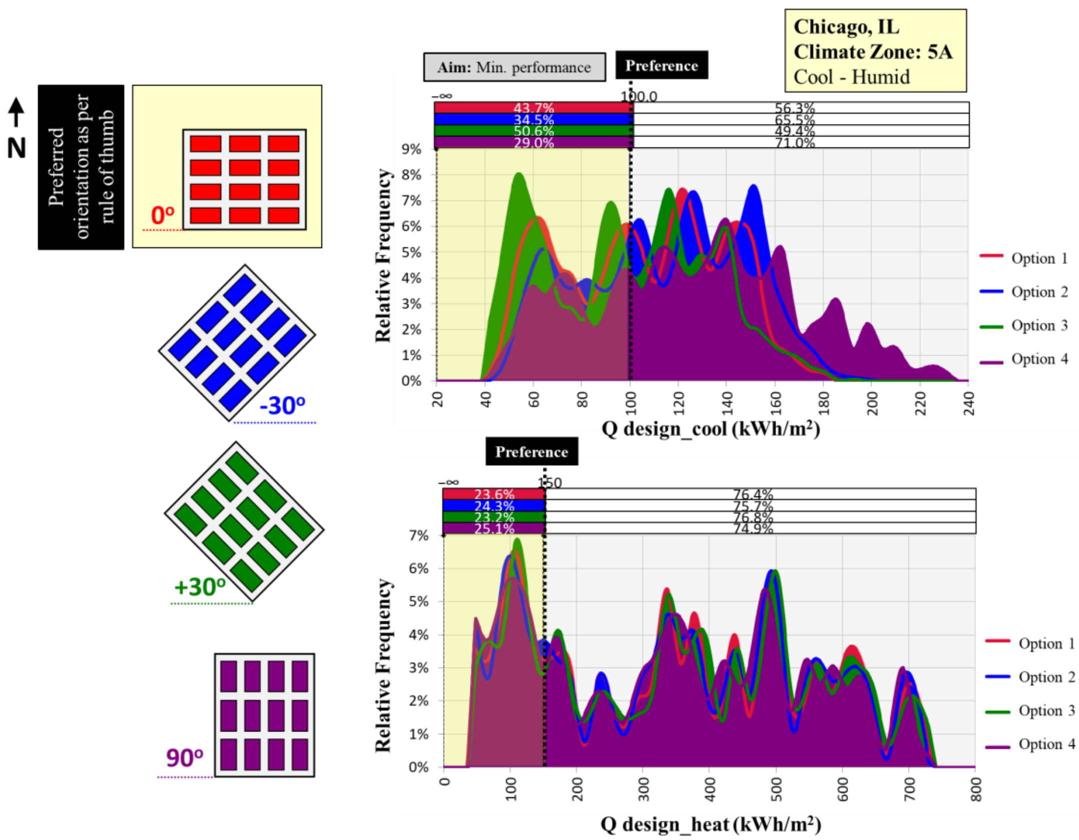



**Figure 6.5: Urban energy consumption (cooling and heating needs) for four different orientation options in Chicago, IL**

Miami is the third location chosen for analysis, which is considered a hot-humid climate zone. There is no heating need in Miami, so only cooling need is compared for different options. As per the rule of thumb recommendation, option 3 is proposed as the best performing option. Based on the performance comparison of all options, it is noted that this recommendation applies as option 3 has the most probability of achieving low cooling energy need as compared to other options (Figure 6.6).

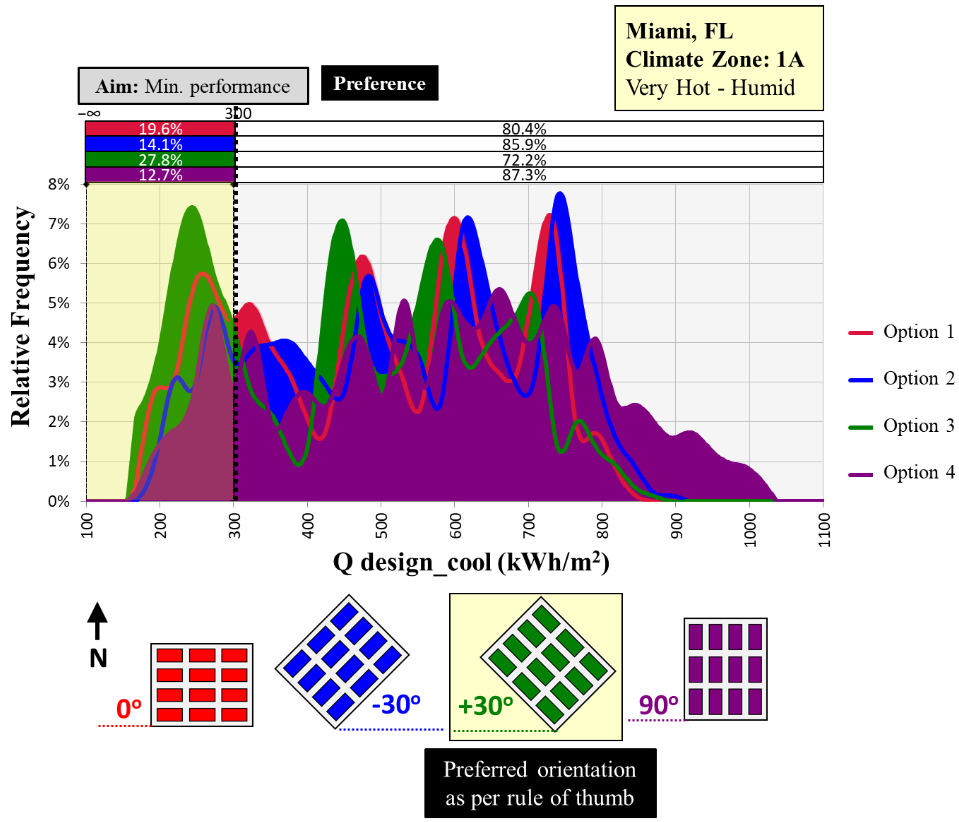



**Figure 6.6: Urban energy consumption (cooling and heating needs) for four different orientation options in Miami, FL**

Another performance measure for which the rule of thumb sets orientation preference is outdoor thermal comfort. Analysis points in the urban void are defined for computation of this measure (Figure 6.7) in the three climate zones. The measure is the percentage of hours comfortable for these analysis points. Its distribution and mean are compared for the four urban fabric orientations. An option with the higher percentage of comfortable hours is considered ‘better’ performing fabric in terms of outdoor thermal comfort.

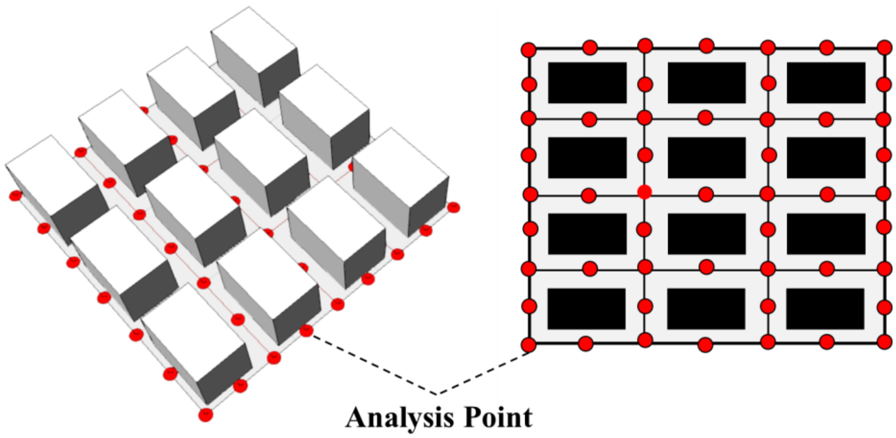



**Figure 6.7: Analysis points in the urban fabric to compute the outdoor thermal comfort performance measure**

The results show that in the three climate zones, the distributions of the predicted outdoor comfort measure are very similar and difference between the four orientations is 2% at most, which is not significant enough to make a decisive decision about urban fabric orientation based on outdoor thermal comfort measure, this is because outdoor thermal comfort is highly impacted by context geometry, which is constant over the options in this example (Figure 6.8, Figure 6.9, Figure 6.10). However, if we consider the overall range of percentage of comfortable hours and compare the slight difference in the overall options, it is noted that for the Atlanta climate zone, option 3 has the highest probability of achieving more comfortable hours, which is conform the rule of thumb recommendation. In Chicago, option 2 has the slightly higher range as compared to other options, but the preferred orientation as per rule of thumb is option 1. Finally, for Miami, the rule-recommended orientation is option 3; however as per the performance analysis, options 1 and 4 have slightly higher probability of achieving more comfortable hours.

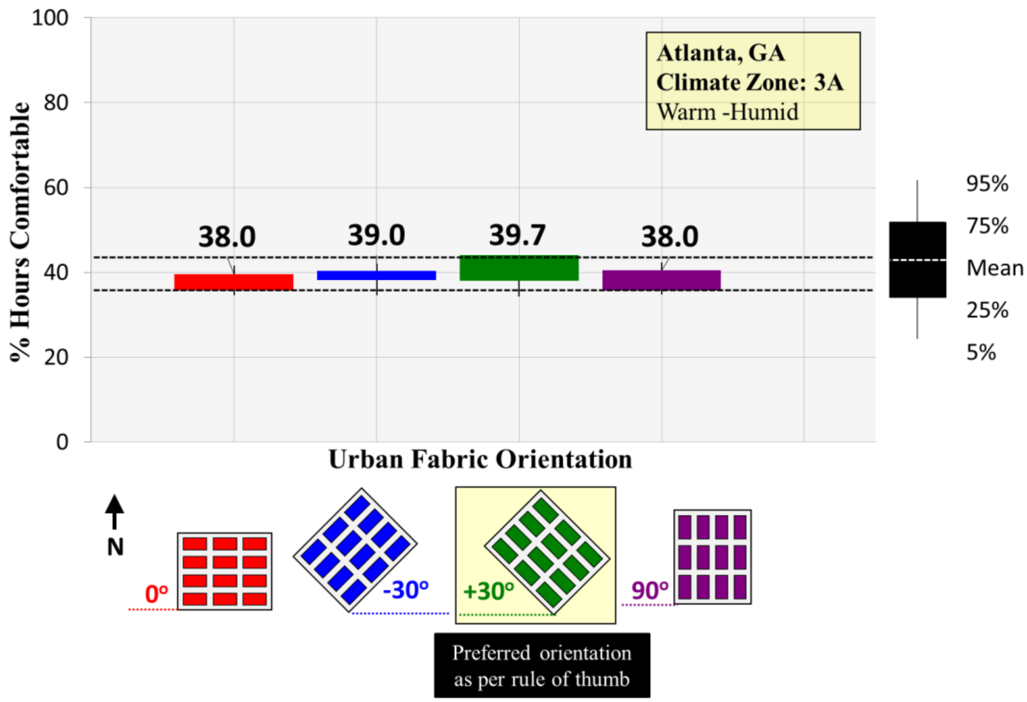



**Figure 6.8: Percentage of comfortable hours for four different orientation options in Atlanta, GA**

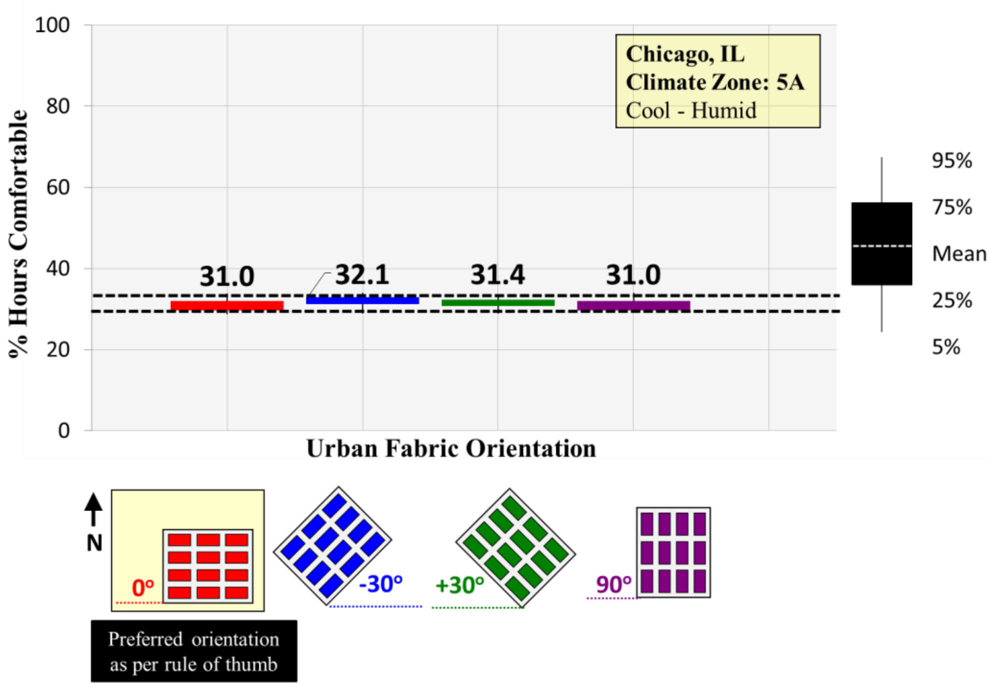



**Figure 6.9: Percentage of comfortable hours for four different orientation options in Chicago, IL**

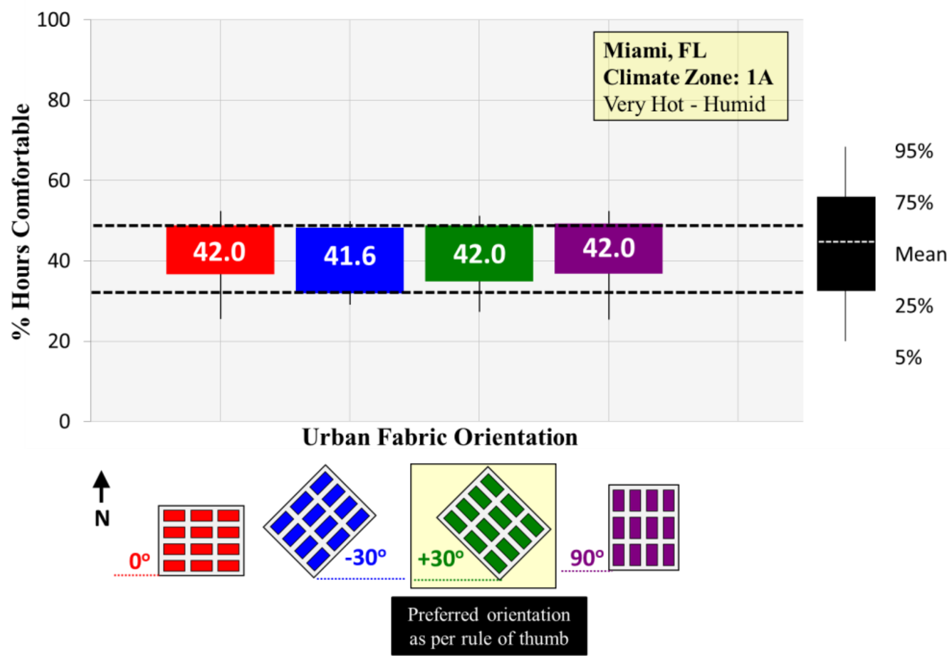



**Figure 6.10: Percentage of comfortable hours for four different orientation options in Miami, FL**

Based on comparison of energy and outdoor thermal comfort performances with rules of thumb recommendations, it can be concluded that the rule of thumb recommendation does not always suggest the "best" available design option.

## 6.4 Conclusion

Currently there is a lack of consistent and systematic methods for decision-making in early urban design. There is no methodology within which designers can validate their decisions and provide confidence levels for the outcomes of their decisions. One of the available approaches for decision making at early design stage are published and sometimes widely accepted 'rules of thumb', where recommendations are proposed for achieving a certain desired performance. However, based on the analysis in this chapter, it is evident that rules of thumb may in some cases provide a false confidence in a suggested design option.

The influence of designers' confidence in a decision is essential during their exploration of the design space and the evolution of a design through decision-making. Providing a level of confidence in a given decision is not considered in current approaches and for the time being, there is no proof that it will enhance the decision making of designers in real settings. This ties in with another important characteristic of urban design which is its iterative and sequential nature of decision making. Although this is accepted and well understood, it is not reflected and supported in the tools of current practice. "Rule of thumb" approaches offer a fast alternative but without explicit expression of confidence in the suggested option in a given setting.

# CHAPTER 7. IMPLEMENTATION

## 7.1 Introduction

In order to increase the applicability of the proposed method, particularly for industry, it needs to be integrated with current computational platforms, and preferably with embedded form generation (CAD) tools. In the development platform, the Rhino-Grasshopper set of tools was chosen for that reason. The platform offers a library that consists of seven components (Figure 7.1): urban generation, design parameter uncertainty quantification (UQ) and five performance measures, which will be discussed in detail in the next section. The results from the performance calculation components are automatically exported to excel files, which can then be used for analysis and comparison of design options.

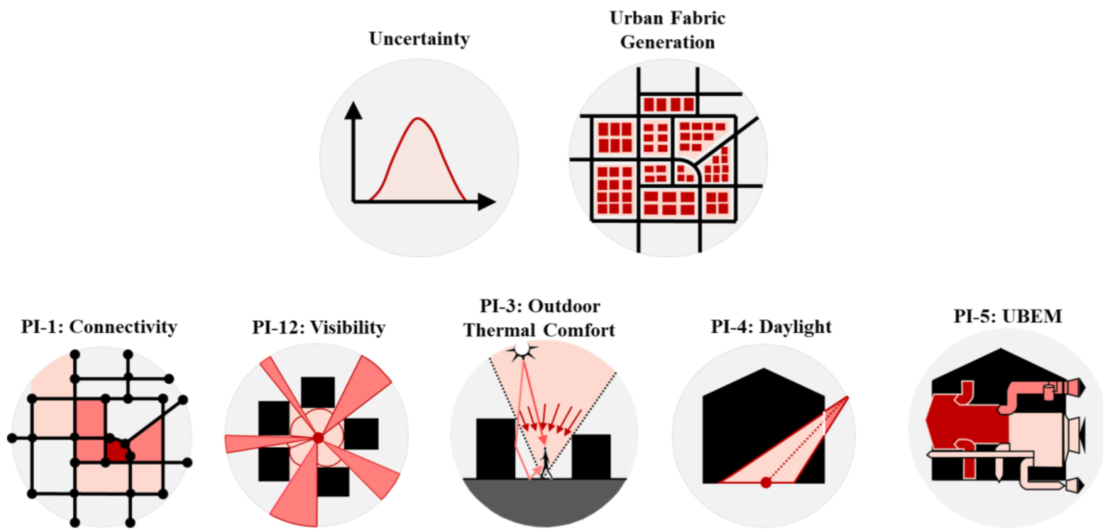



**Figure 7.1: Library for Rhino-Grasshopper interface**

## 7.2 Grasshopper Components

### *7.2.1 Urban Fabric Generation*

Urban fabric generation component is used for generating urban fabric based on design parameters. The input parameters for this component are:

- *Site boundary*: polyline defining the site boundary.
- *Street Network*: multiple lines representing street network.
- *Block Offset*: a number representing block setback from street in meters.
- *Parcel Width*: a number representing the maximum parcel width facing the street in meters.
- *Road, side, back setback*: a number value for buildable area outline setback from all sides in meters.
- *Floor Height*: a number representing floor to floor height in meters.
- *Building Type*: a choice from 3 building type options, which are: freestanding, row-house and courtyard.

The resultant output is an urban fabric populated with the following elements:

- *Block:* a 2d line representation of urban block.
- *Parcel:* a 2d line representation of parcel outline.
- *Buildable Area:* a 2d line representation of buildable area outline.
- *Building:* a 3d geometry representing building.

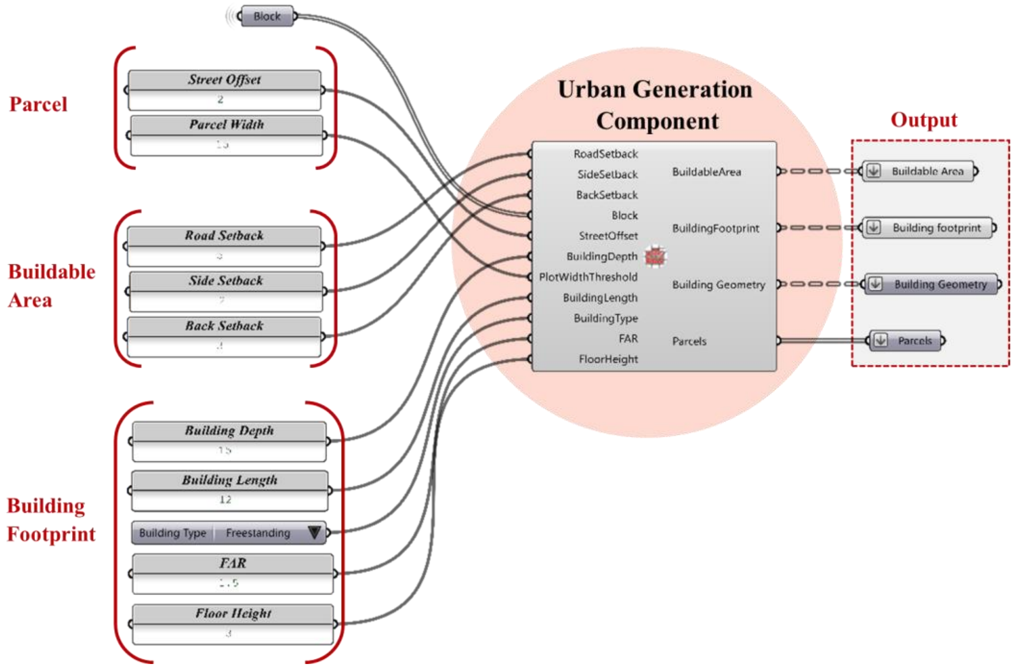



**Figure 7.2: Urban generation data flow**

### *7.2.2 Design Parameter Uncertainty Quantification*

The parameter UQ component offers ranges and distributions of the design parameters across the design space at a given decision moment. At this stage of the development, this component only uses designer specified inputs. The needed input data for this component are as following:

- *Parameter Range:* two number values representing upper and lower limits of design parameter.
- Parameter Range Distribution: a graph representing the parameter distribution type.

Multiple parameter ranges and distributions can be added as input based on the number of uncertain design parameters and the output is a list of possible design parameter combinations, each representing an alternative combination of values, hence generating 'combinatorial parameter space', which are used as input for urban generation component and performance measure components. The combinatorial parameter space is translated into the samples that are the input in the Monte Carlo based simulations in the performance calculations.

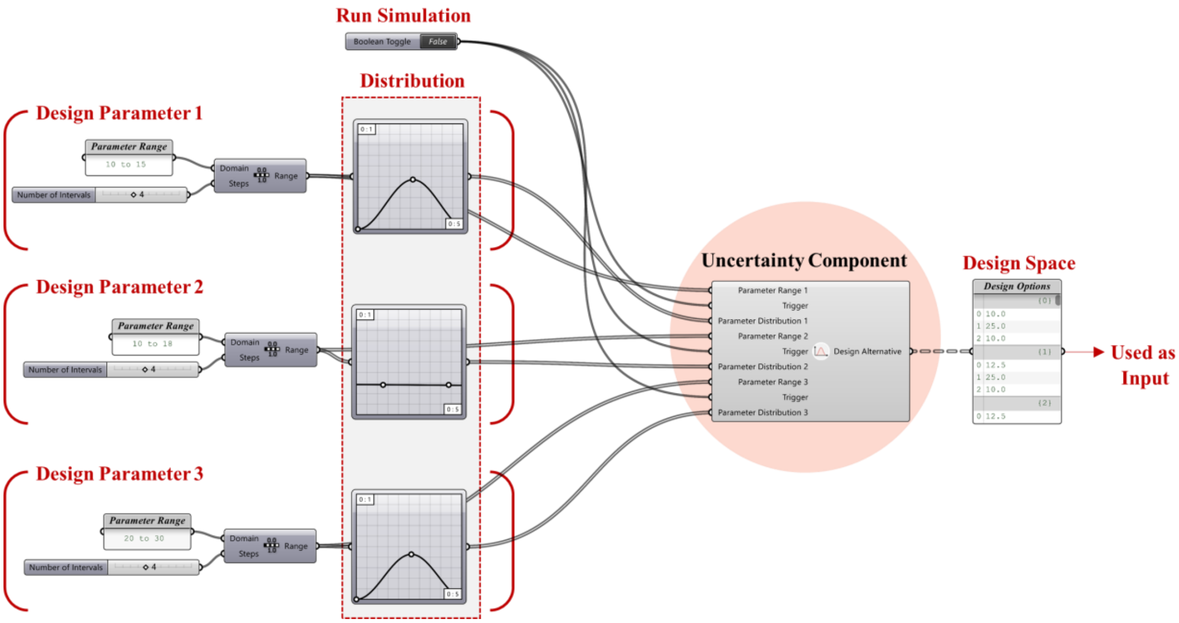



**Figure 7.3: Uncertainty Quantification data flow**

### *7.2.3 Network Connectivity Component*

The network connectivity component executes the performance measure computation which is detailed in section 4.4.1. The input parameters needed for this component are:

- *Street Network:* multiple lines representing street network.
- *Origin:* nodes that exemplify entry points to the site.
- *Destination:* nodes representing activity points within the site.

The output of this component is a numeric value assigned to each street network and parcel in the urban fabric, which are summed up to compute percentage of used network and percentage of by-pass product. The following are the output values of the component:

- *Street Connectivity:* a numeric value representing frequency of use of each street line.
- *Parcel by-pass value:* a numeric inherited from adjacent street line, hence indicating frequency of by passing each parcel.
- *Percentage of used network:* a number representing percentage of street lines used from the total street lines in the urban fabric.
- *Percentage of by-pass product:* numeric value indicating percentage of parcels with by-pass value from the total parcels in the urban fabric.

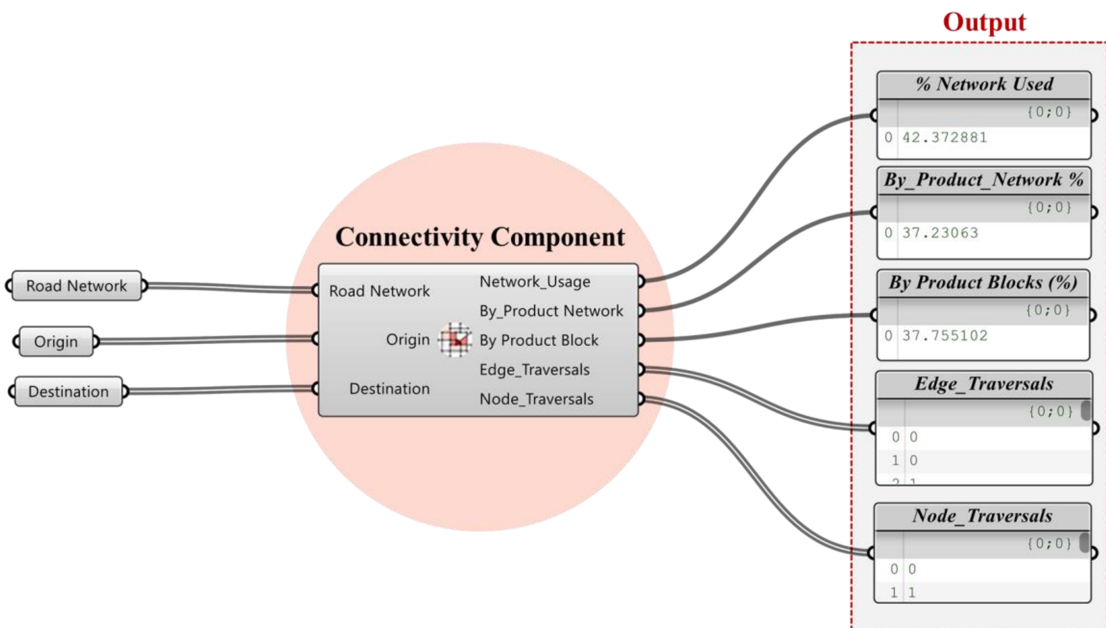



**Figure 7.4: Connectivity component data flow**

### *7.2.4 Visibility Component*

The visibility component is used for performance measure computation as detailed in section 4.4.2 the input parameters used for this component are as following:

- *Obstacle:* 3d geometry representing buildings.
- *Analysis Points*: point used as station points for analysis.

- *View Radius*: maximum view distance from analysis point in meters.

The output of this component has both geometric and numeric values as following:

- *Total Visibility:* total amount of area visible from analysis point in square meters.
- *Total Complexity:* perimeter length of total amount of area visible from analysis point in meter.
- *View Cone Geometry:* 2 lines and an arc representing vision cones from analysis points.
- *View Angle:* angle of each generated view cone.
- *View Distance:* maximum length of each generated view cone.
- *Unobstructed Percentage:* percentage of view cones area that are not obstructed by building geometry.

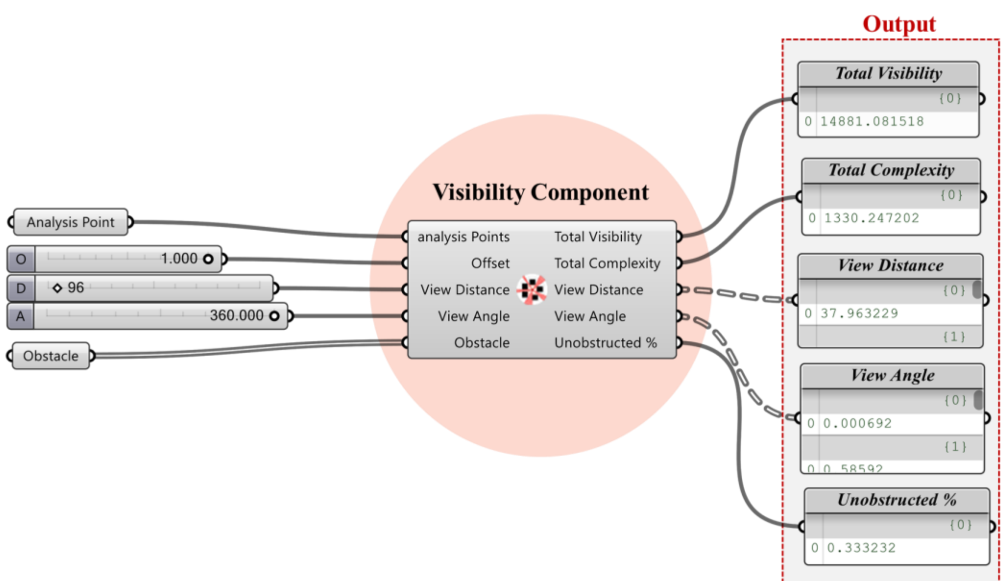



**Figure 7.5: Visibility component data flow**

### *7.2.5 Outdoor Thermal Comfort Component*

The outdoor thermal comfort component is a performance measure calculation, as detailed in section 4.4.3. The component requires the following input:

- *Weather file:* file path for a TMY weather file.
- *Latitude and Longitude:* numeric value for latitude and location representing site location.
- *Analysis Period:* start and end of analysis period in month, day and hour
- *Context:* 3d geometry representing buildings in the urban fabric.
- *Analysis Plane:* 2d geometric boundary representing analysis plane.

The input parameters are used to compute the following numeric output values:

- *ERF:* Effective radiant field (W/m$^2$).
- *dMRT:* temperature addition to air temperature (°C).
- *MRT:* mean radiant temperature (°C).
- *Percentage of Comfortable hours:* percentage of hours within the analysis period that are within comfort range as defined by UTCI.

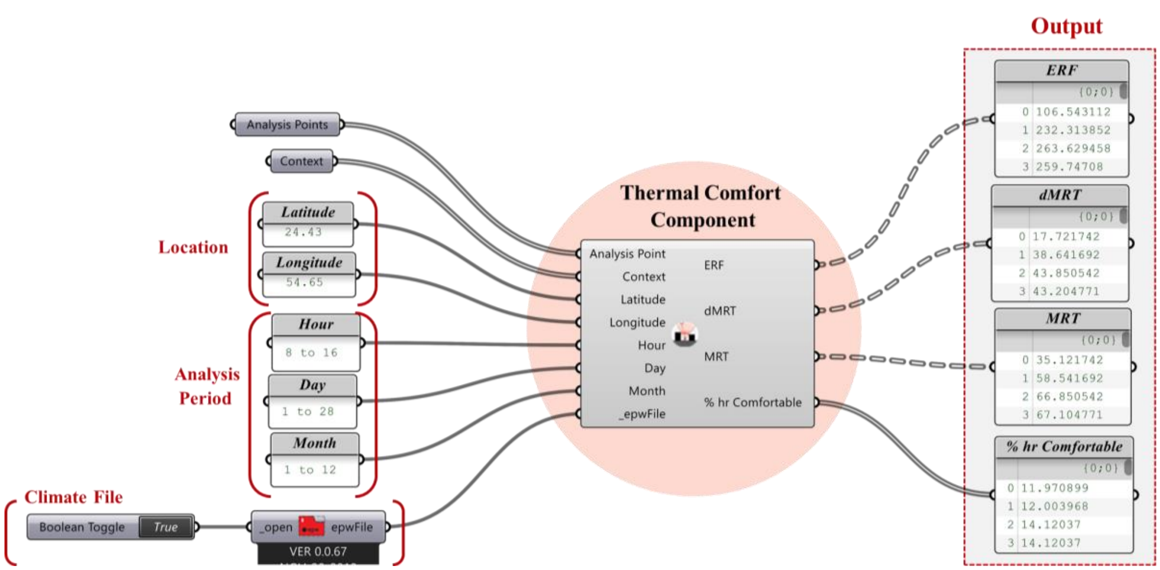



**Figure 7.6: Outdoor thermal comfort component data flow**

*7.2.6 Daylight Component*

The daylight component is a performance measure computation for interior daylight in buildings, as detailed in section 4.4.4. The input parameters needed for running this component are as following:

- *Weather file:* file path for a TMY weather file.
- *Analysis Period:* start and end of analysis period in month, day and hour
- *Context:* 3d geometry representing buildings in the urban fabric.
- *WWR:* window-to-wall ratio for each façade (South, North, East, West).

The following are the output values of this component:

- *Façade Illuminance:* illuminance level on the façade in lux.
- *Interior Illuminance:* illuminance level inside building in lux.
- *Percentage of hours above 300 lux:* percentage of hours from the total analysis hours that have an interior illuminance level of more than 300 lux.

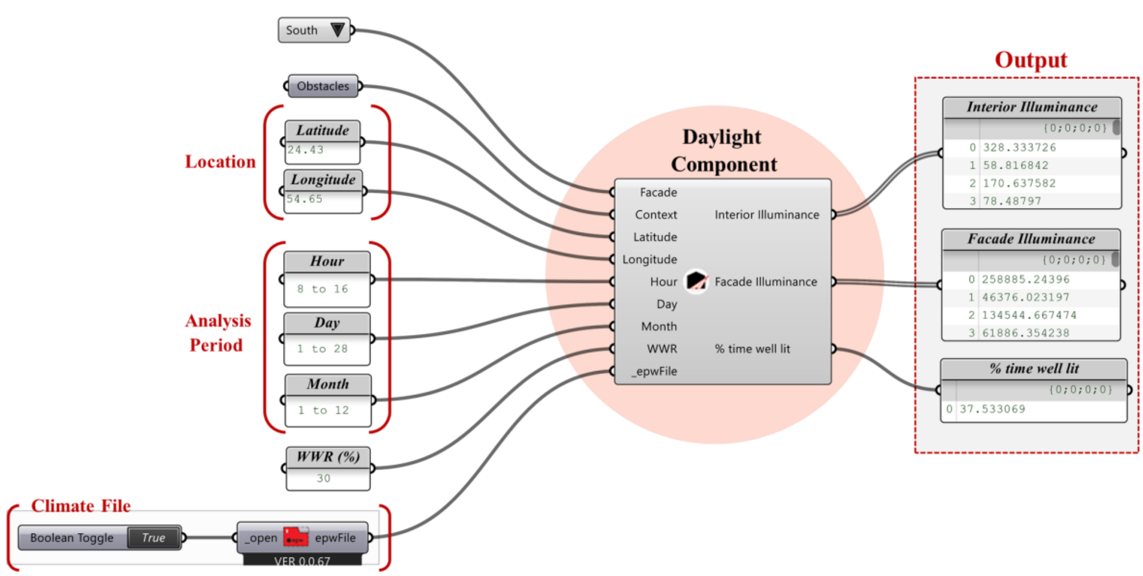



**Figure 7.7: Daylight component data flow**

### *7.2.7 Urban Building Energy Component*

The urban building energy component calculates building energy needs as detailed in section 4.4.5. The following are the input data needed for this component:

- *Weather file:* file path for a TMY weather file.
- *Context:* 3d geometry representing buildings in the urban fabric.
- *Envelope Properties*: Roof, Wall, Window U-value, absorption and emissivity.
- *Building Use*: type of building use is used to define internal loads (residential, commercial, industrial).

Based on the input parameters, the following outputs are computed:

- *Cooling Need:* Building cooling energy need (kWh/m$^2$).
- *Heating Need:* Building heating energy need (kWh/m$^2$).

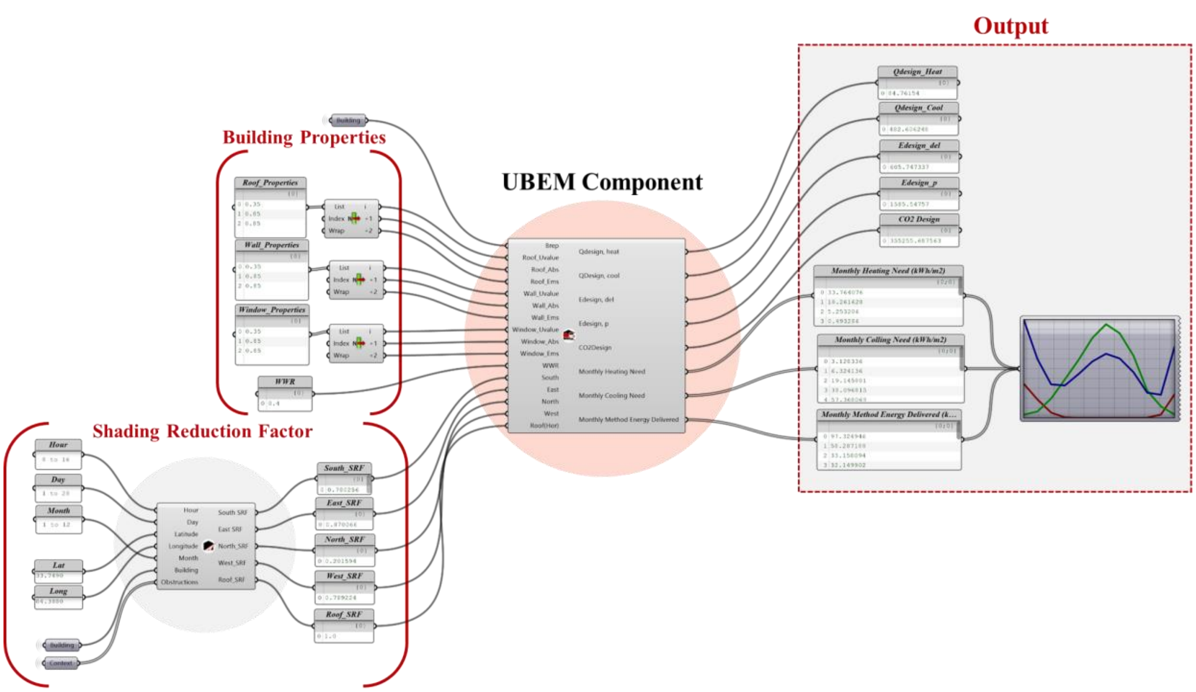



**Figure 7.8: Urban building energy component data flow**

## 7.3 Discussion

The methodology developed in this thesis is packaged as Rhino-grasshopper components in order to test and showcase its application. Choosing this platform increases its chance to be applied in the real urban design problems by making the approach accessible for designers. This community is increasingly, adopting grasshopper platforms in their work.

The components can easily be linked to the geometry created in Rhino environment, making it approachable for designers that are familiar with this platform. It should be noted that the performance measure components are stand alone, so that they can be used as per project requirement, and/or integrated in other grasshopper-based developments. Other performance measures could be easily added to the existing platform.

The platform discussed above serves primarily to demonstrate the effectiveness and verify the applicability of the development methodology for performance-based urban design decision making. Obviously, there are alternative computational platforms with which the methodology can be implemented. One associated issue to consider is the use of normative calculation methods as discussed before. If the point can be made that more elaborate high-order simulations are required for certain performance measures, a grasshopper platform may prove to be less efficient and other closed form software architectures may be the preferred road forward.

# CHAPTER 8. CONCLUSION

## 8.1 Summary & Conclusion

Urban design currently lacks a systematic approach to rational decision-making at the early stage of design. There is no practical framework within which designers can generate and evaluate promising alternatives regarding with respect to a set of urban performance measures, nor are there suitable algorithms with which designers can validate their decisions in terms of unbiased confidence in their decisions in early design stage. It is argued that the latter is essential in the exploration of design alternative and progress of design process through rational decision-making. This is not offered in current approaches. Current urban performance analysis models are deterministic, and their typical use is as a consequence limited to deterministic evaluation of design alternatives under default assumptions of extraneous undecided design variables. This implies that design variables are assumed to be known with certainty, which is normally not the case, especially in early design. In addition to that, the iterative nature of design and sequential but interdependent process of decision-making is insufficiently reflected in current practice.

To overcome these deficiencies in current performance-based urban design, this study develops a new approach based on the systematic comparison of alternative design proposals with explicit quantification of design uncertainties. This approach is executed in a platform based on a simple urban generation model and normative performance models that take design parameter uncertainty into consideration at different stages of decision-making. In contrast to the conventional urban performance analysis approaches in which both input design parameters and output performance measure are deterministic values, the proposed method deals with design parameters and performance measures as probability distributions.

Towards developing normative performance models, relevant measures are first extracted from established literature and simplified calculation methods proposed for them. These models are then tested individually on simple urban fabrics (Section 4.4). Finally, the proposed framework with multiple performance measures are tested on two real case studies (Chapter 5).

Applying the proposed approach helps designers in:

- Providing a clear stepwise approach in urban design that support exploration of options and their performance evaluation.
- Highlighting significant design parameters that impact different urban performance measures.
- Incorporating undecided design parameter uncertainty as fundamental concept and driver in decision-making at the early stage of design, when the level of unknowns, undecided, and subsequently uncertainties are high, and providing confidence in a decision is of importance.
- Embodying the iterative nature of urban design in the approach by updating information as new decisions are made and accommodating new requirements and preferences as design progresses.
- Enabling designers to define different performance objectives (translated into targets of performance value) based on project requirements and thereby constrain the design solution space accordingly.
- Increasing generic design knowledge by determining which and how design variables impact the different urban performances.
- Maintaining design freedom and providing potentially larger design solution space compared to current approaches. This is related to the fact that current deterministic approaches tend to favor a certain variant whereas in reality there is no rational reason to favor this variant over others when design uncertainties are considered.

The latter point is exemplified by a study that compares the proposed method with a currently used "rule of thumb" at the early design stage. Not unexpected, the study proves that the confidence provided by "rule of thumb" recommendations is not always reliable because of the uncertainty in undecided design parameters.

The methodology is implemented in Rhino-grasshopper platform which offers benefits with regard to analysis time and computational effort. The platform packages as grasshopper components: urban generation, design parameter uncertainty and five performance measure components. The time to run each possible design option based on the parameter uncertainty varies from 5 to 10 seconds based on the performance measure, and it does not require special expertise in the field of optimization and statistics in order to run the analysis and interpret results. This research contributes to the body of knowledge pertaining to the performance of urban fabric and decision making at the early design stage. Its framework can be used by researchers in academia, by urban designers in industry, as well as by policy makers at the in-city level. The developed components can be easily integrated in other computational environments.

## 8.2 Future Work

- *Expanding normative urban performance measures*: Urban design is a multi-objective decision problem. In this thesis five performance measures were chosen as the basis of the demonstration and verification of the approach. It is intended to expand the library of these normative measures.

- *Generalizing the uncertainty quantification*: In its current form, the platform relies on designer input for the representation (distributions) of design uncertainties. The knowledge and insight that is required to do this cannot be expected from practicing urban designers. Moreover, it potentially adds a significant bias to the uncertainty specification which should be avoided as it would nullify the benefit of the rationalization of the decision making. Future work should therefore focus on the development of generic UQ repositories of urban design parameters. Such studies can be performed by analyzing many urban designs and use categorization and clustering to derive the uncertainty distributions by setting, location, intent and possible other. Alternative methods used in the past can take certain post measurements of a large number of developed urban plans and perform an inverse identification technique to determine the parameter distribution. An example of this technique, applied to building design parameters can be found in (Zhao, 2012).

- Further testing and validation by practicing urban designers is obviously an important next step in the development. Such tests would have to be conducted in two stages i.e. (1) test in an in-vitro environment with real designers, (2) adaptation based on this test, (3) test in a real-life setting. Obviously, this will require substantial resources and careful design of the three test stages.

- *Application of proposed method in urban retrofit strategy analysis:* The proposed approach has been explored for new designs only. It is intended to further develop it to accommodate urban retrofit projects to explore different strategies.

- *Adaptive performance driven urban design*: A Rhino interface could be developed that allows to monitor performance measures instantaneously as design progresses based on automatic feedback from the embedded performance components. In addition, all design variants would be automatically ranked with explicit confidence levels. This would fully integrate the developed methodology in the urban design generation environment. The latter seems a far-out target by any stretch.

# APPENDIX A: PERFORMANCE MEASURE-1, CONNECTIVITY SIMULATION RESULT VISUALIZATION

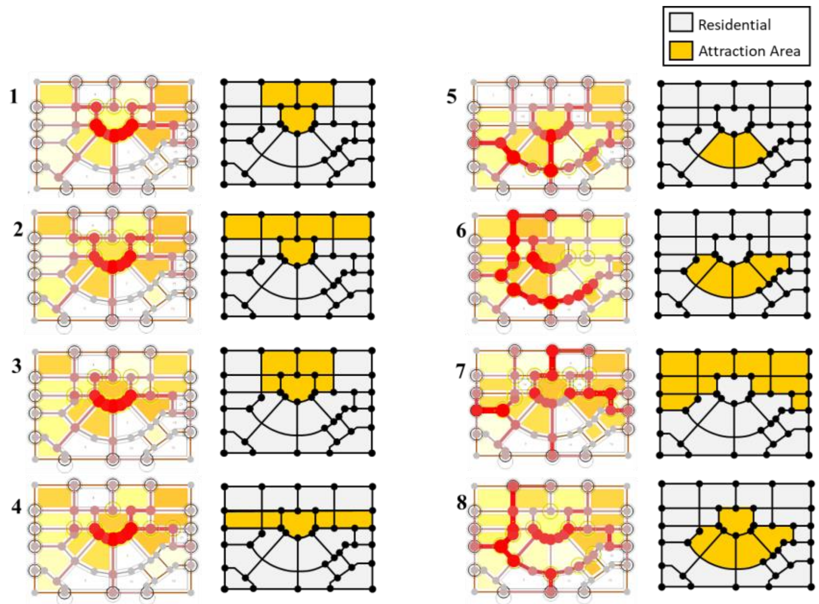



**Figure A.0.1: Case study 1 land use options and their connectivity simulation results**

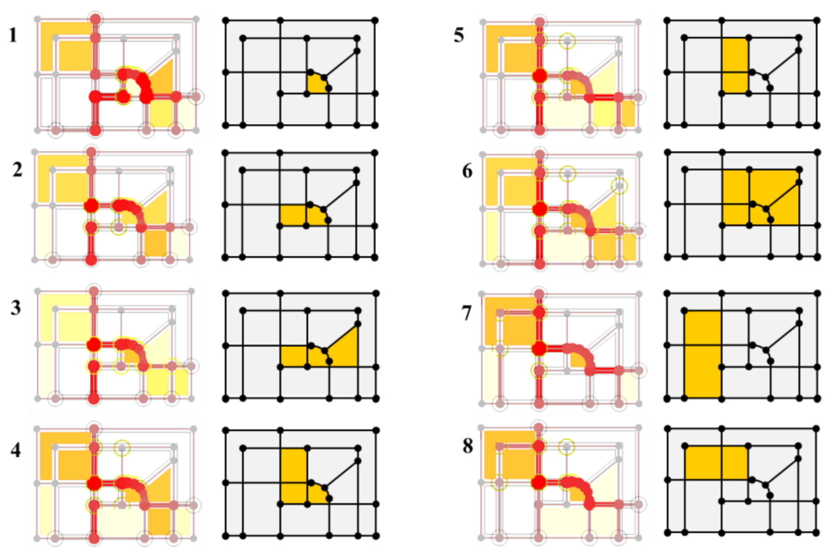



**Figure A.0.2: Case study 2 land use options and their connectivity simulation results**

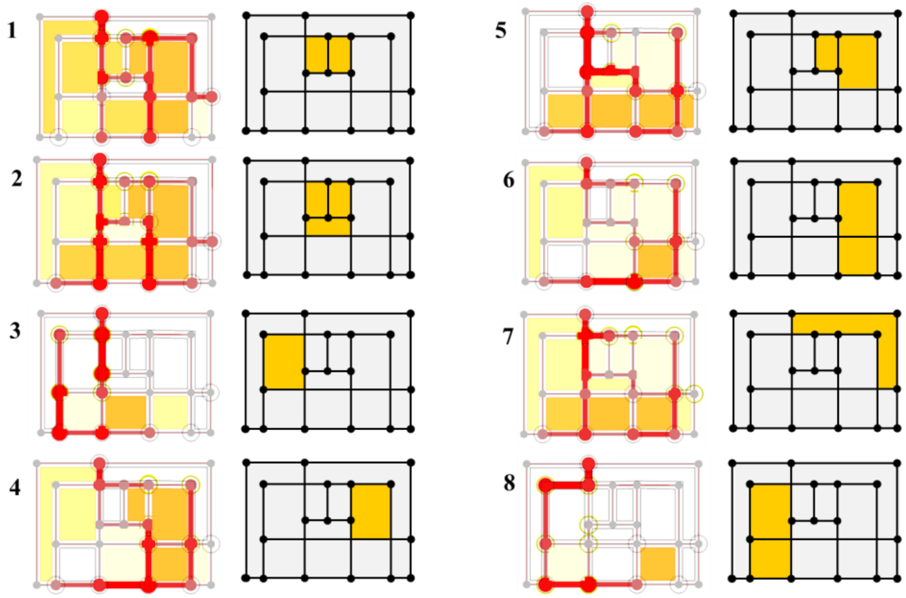



**Figure A.0.3: Case study 3 land use options and their connectivity simulation results**

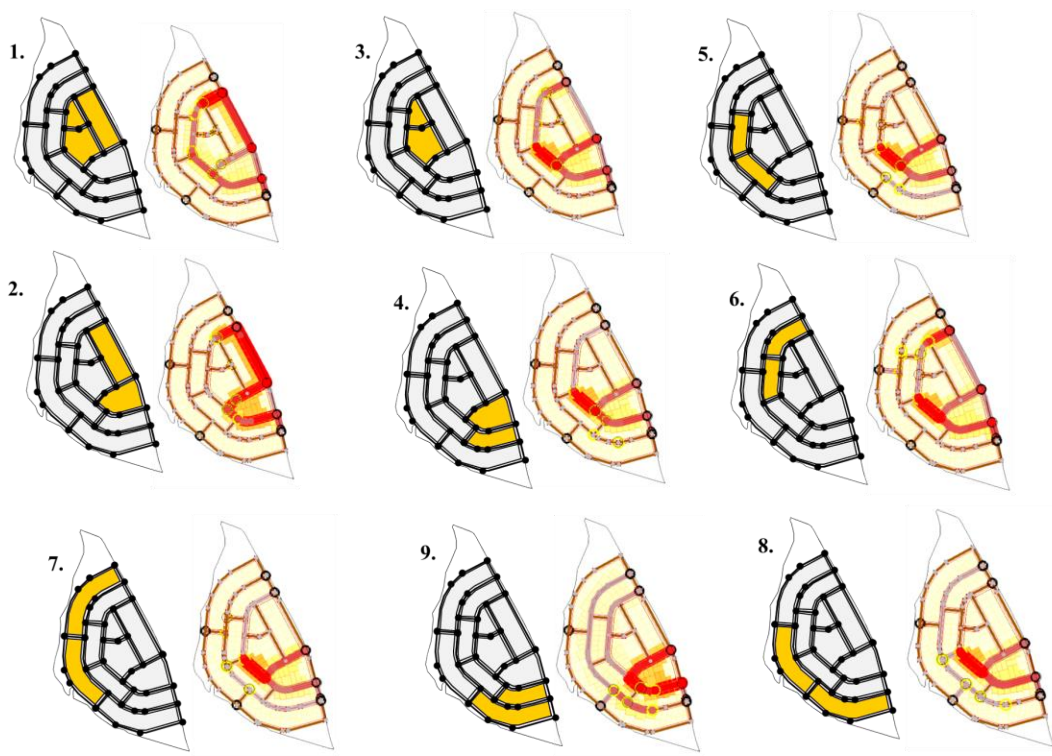



**Figure A.0.4: Real case study 1 land use options and their connectivity simulation results (Street network option 1)**

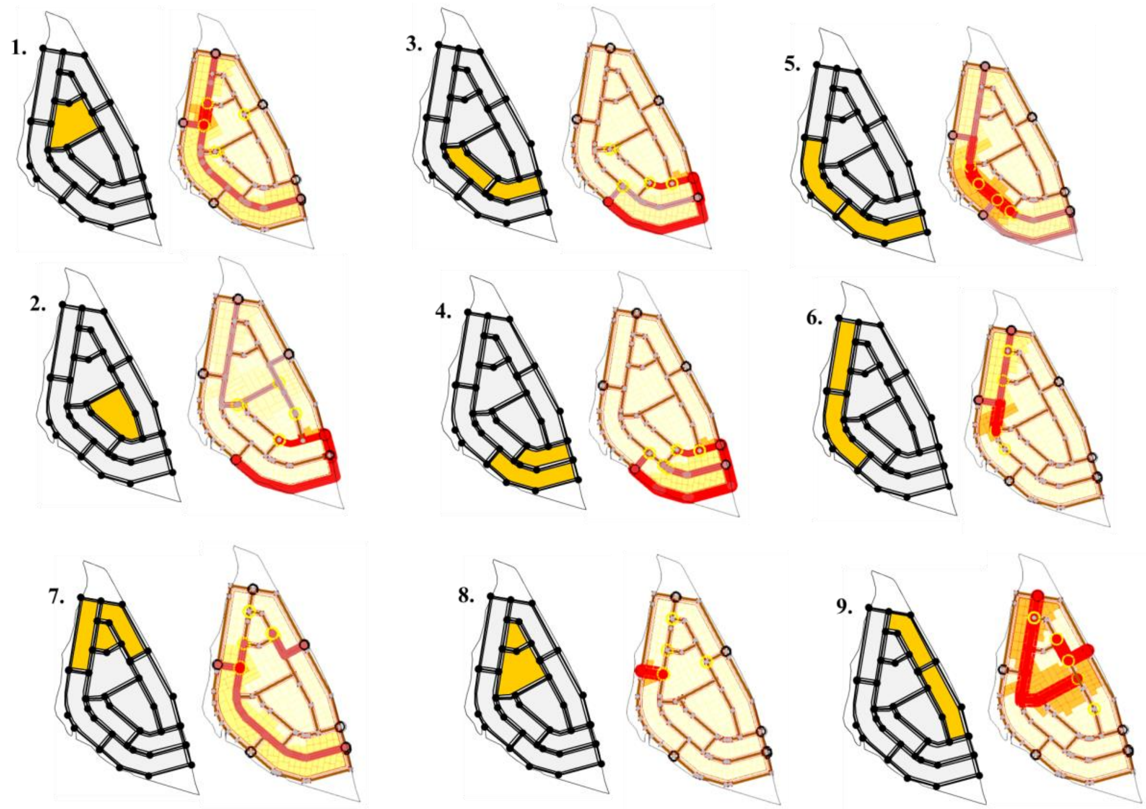



**Figure A.0.5: Real case study 1 land use options and their connectivity simulation results (Street network option 2)**

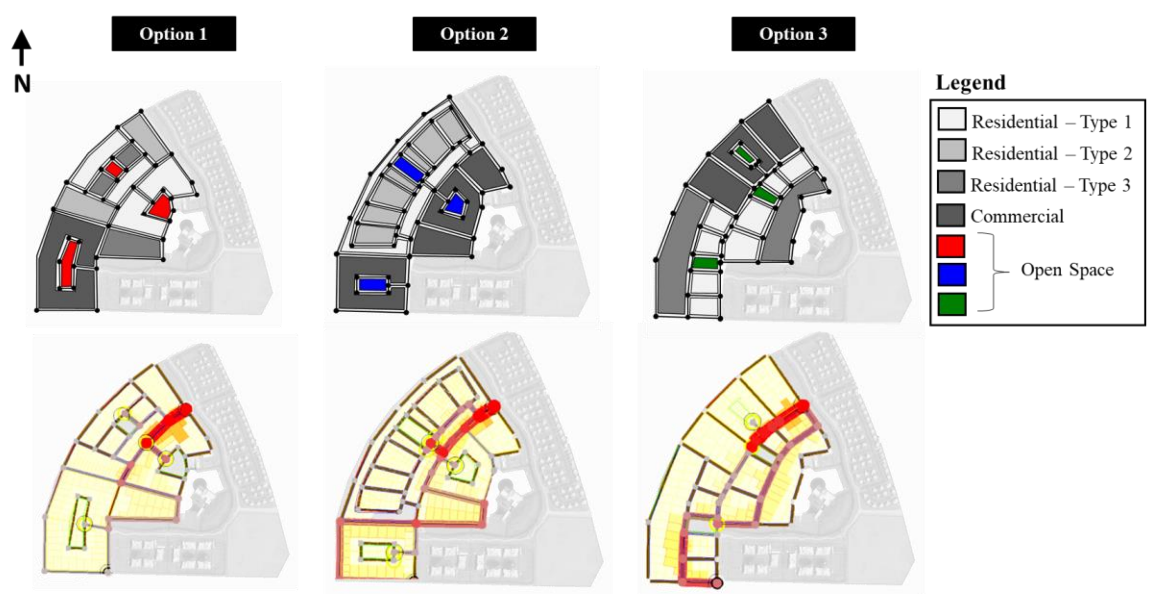



**Figure A.0.6: Real case study 2 land use options and their connectivity simulation results**

# APPENDIX B: THERMAL COMFORT WILCOXON TEST

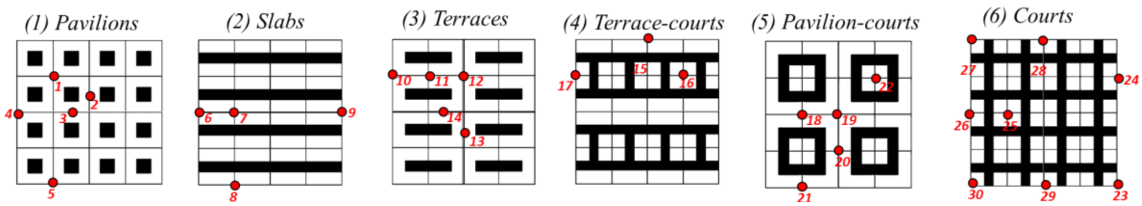



**Figure B.0.1: Analysis points for outdoor thermal comfort simulation**

**Table B.1: Outdoor thermal comfort analysis results**

| | | % Time Comfortable | | | | | | |
|---|---|---|---|---|---|---|---|---|
| **Case** | **Pt** | **Ladybug** | **Proposed Model** | **delta** | **abs_delta** | **rank** | **T_pos** | **T_neg** |
| **1** | 0 | 20.767196 | 22.321429 | 1.554233 | 1.554233 | 15 | 15 | 0 |
| **2** | 1 | 21.329365 | 19.907407 | -1.42196 | 1.421958 | 12 | 0 | 12 |
| **3** | 2 | 24.900794 | 28.240741 | 3.339947 | 3.339947 | 22 | 22 | 0 |
| **4** | 3 | 13.359788 | 11.772487 | -1.5873 | 1.587301 | 16 | 0 | 16 |
| **5** | 4 | 10.846561 | 10.714286 | -0.13228 | 0.132275 | 2 | 0 | 2 |
| **6** | 0 | 13.789683 | 14.451058 | 0.661375 | 0.661375 | 8 | 8 | 0 |
| **7** | 1 | 21.46164 | 26.719577 | 5.257937 | 5.257937 | 26 | 26 | 0 |
| **8** | 2 | 11.111111 | 11.177249 | 0.066138 | 0.066138 | 1 | 1 | 0 |
| **9** | 3 | 16.964286 | 23.015873 | 6.051587 | 6.051587 | 28 | 28 | 0 |
| **10** | 0 | 11.739418 | 10.218254 | -1.52116 | 1.521164 | 13 | 0 | 13 |
| **11** | 1 | 19.444444 | 25.462963 | 6.018519 | 6.018519 | 27 | 27 | 0 |
| **12** | 2 | 16.997354 | 18.518519 | 1.521165 | 1.521165 | 14 | 14 | 0 |
| **13** | 3 | 13.921958 | 15.542328 | 1.62037 | 1.62037 | 17 | 17 | 0 |
| **14** | 4 | 19.279101 | 26.025132 | 6.746031 | 6.746031 | 30 | 30 | 0 |
| **15** | 0 | 19.742063 | 26.157407 | 6.415344 | 6.415344 | 29 | 29 | 0 |
| **16** | 1 | 26.488095 | 28.80291 | 2.314815 | 2.314815 | 20 | 20 | 0 |
| **17** | 2 | 15.47619 | 15.244709 | -0.23148 | 0.231481 | 5 | 0 | 5 |
| **18** | 0 | 27.380952 | 29.100529 | 1.719577 | 1.719577 | 18 | 18 | 0 |
| **19** | 1 | 20.039683 | 22.156085 | 2.116402 | 2.116402 | 19 | 19 | 0 |
| **20** | 2 | 24.636243 | 23.842593 | -0.79365 | 0.79365 | 9 | 0 | 9 |
| **21** | 3 | 11.177249 | 11.309524 | 0.132275 | 0.132275 | 2 | 2 | 0 |
| **22** | 4 | 21.097884 | 25.231481 | 4.133597 | 4.133597 | 24 | 24 | 0 |
| **23** | 0 | 10.747354 | 10.582011 | -0.16534 | 0.165343 | 4 | 0 | 4 |
| **24** | 1 | 20.138889 | 24.636243 | 4.497354 | 4.497354 | 25 | 25 | 0 |
| **25** | 2 | 26.488095 | 28.80291 | 2.314815 | 2.314815 | 20 | 20 | 0 |
| **26** | 3 | 16.104497 | 15.244709 | -0.85979 | 0.859788 | 10 | 0 | 10 |
| **27** | 4 | 14.781746 | 13.822751 | -0.959 | 0.958995 | 11 | 0 | 11 |
| **28** | 5 | 24.305556 | 27.810847 | 3.505291 | 3.505291 | 23 | 23 | 0 |
| **29** | 6 | 11.805556 | 12.037037 | 0.231481 | 0.231481 | 5 | 5 | 0 |
| **30** | 7 | 10.813492 | 10.548942 | -0.26455 | 0.26455 | 7 | 0 | 7 |
| | | | | | | **Sum** | **345** | **71** |
| | | | | | | | *T+ve* | *T-ve* |

**Table B.2: Critical values of Wilcoxon signed ranks test**

| n | Two-Tailed Test | | One-Tailed Test | |
|---|---|---|---|---|
| | α = .05 | α = .01 | α = .05 | α = .01 |
| 5 | -- | -- | 0 | -- |
| 6 | 0 | -- | 2 | -- |
| 7 | 2 | -- | 3 | 0 |
| 8 | 3 | 0 | 5 | 1 |
| 9 | 5 | 1 | 8 | 3 |
| 10 | 8 | 3 | 10 | 5 |
| 11 | 10 | 5 | 13 | 7 |
| 12 | 13 | 7 | 17 | 9 |
| 13 | 17 | 9 | 21 | 12 |
| 14 | 21 | 12 | 25 | 15 |
| 15 | 25 | 15 | 30 | 19 |
| 16 | 29 | 19 | 35 | 23 |
| 17 | 34 | 23 | 41 | 27 |
| 18 | 40 | 27 | 47 | 32 |
| 19 | 46 | 32 | 53 | 37 |
| 20 | 52 | 37 | 60 | 43 |
| 21 | 58 | 42 | 67 | 49 |
| 22 | 65 | 48 | 75 | 55 |
| 23 | 73 | 54 | 83 | 62 |
| 24 | 81 | 61 | 91 | 69 |
| 25 | 89 | 68 | 100 | 76 |
| 26 | 98 | 75 | 110 | 84 |
| 27 | 107 | 83 | 119 | 92 |
| 28 | 116 | 91 | 130 | 101 |
| 29 | 126 | 100 | 140 | 110 |
| 30 | 137 | 109 | 151 | 120 |

W_stat = smaller (T+ve/T-ve) = **71**

W_crit (α = 0.05, n=30) = **137**

W_stat < W_crit → Accept $H_0$

**$H_0$** → Median difference =0 ($M_1 = M_2$)

# APPENDIX C: PROPOSED APPROACH APPLICATION

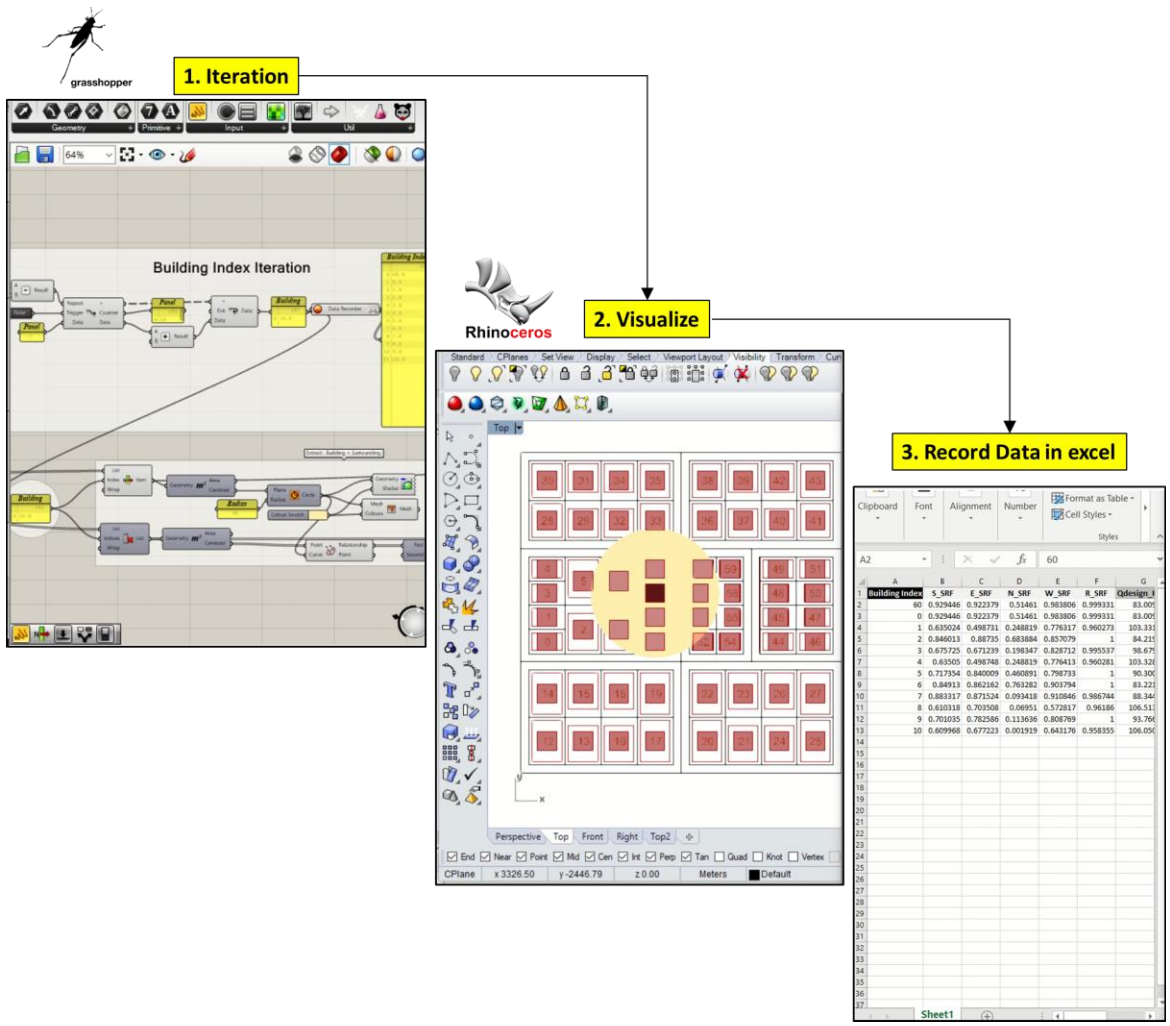



**Figure C.0.1: Proposed approach application workflow**

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